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Adaptive Trust Modeling in Multi-Agent Systems: Utilizing Experience and Reputation

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Adaptive Trust Modeling in Multi-Agent Systems: Utilizing Experience and Reputation

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Dedication

To my husband, Stephen, whose love is continual evidence of the Father's work in his life

And to my Lord and Savior, Jesus Christ, who enabled me to accomplish this effort.

"Blessed be the name of God, forever and ever. He knows all, does all: He changes the seasons and guides history, He raises up kings and also brings them down, he provides both intelligence and discernment, He opens up the depths, tells secrets, sees in the dark—light spills out of him! God of all my ancestors, all thanks! All praise! You made me wise and strong. And now you've shown us what we asked for. You've solved the king's mystery."
Daniel 2:20-23 (*The Message*)

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Adaptive Trust Modeling in Multi-Agent Systems: Utilizing Experience and Reputation

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Trust among individuals is essential for transactions. A human or software agent in need of resources may reduce transaction risk by modeling the trustworthiness of potential partners. Experience- and reputation-based trust models have unique advantages and disadvantages depending on environment factors, including availability of experience opportunities, trustee trustworthiness dynamics, reputation accuracy, and reputation cost. This research identifies how trusters may utilize both experience- and reputation-based trust modeling to achieve more accurate decision-making tools than using either modeling technique alone. The research produces: 1) the Adaptive Trust Modeling technique for combining experience- vs. reputation-based models to produce the most accurate aggregated model possible, 2) a quantitative analysis of the tradeoffs between experience- and reputation-based models to determine conditions under which each type of model is favorable, and 3) an Adaptive Cost Selection algorithm for assessing the value of trust information given acquisition costs. Experiments show that Adaptive Trust Modeling yields an aggregate trust model more accurate than either experience- or reputation-based modeling alone, and Adaptive Cost Selection acquires the optimal combination of trust information, maximizing a truster's transaction payoff while minimizing trust information costs. These tools enable humans and software agents to make effective trust-based decisions given dynamic system conditions.

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Chapter 1

INTRODUCTION

Trust among individuals is essential for transactions. Often an individual does not have the resources—such as tangible goods, information, or services—to accomplish its goals alone. In these cases, the individual may obtain needed resources through transactions with others. In a transaction, two individuals make an (implicit or explicit) exchange agreement; however, the individuals are exposed to risk, since one or both of the transaction partners may fail to execute the transaction according to the exchange agreement [Fullam, et al., 2005a]. A partner's failure to fulfill a transaction may be unintentional, for example, if the partner miscalculates its ability to meet the terms of the exchange agreement. Alternatively, a partner may intentionally sabotage the transaction, perhaps for a monetary benefit or to harm a partner who is also a competitor.

An individual in need of resources can reduce its risk by assessing the trustworthiness of potential transaction partners, conducting transactions with those partners most likely to fulfill agreements. To select the most trustworthy partners, an individual must be able to both 1) model the trustworthiness of potential transaction partners, and 2) make trust-based decisions based on those models [Fullam, et al., 2005a]. Trust models assist an individual in predicting the outcome of transactions, while trust-based decision-making enables an individual to select the best transaction partners and avoid risky transactions.

This research examines trust within the context of software agents. Agents are proactive, autonomous pieces of software that sense, act, and interact (with humans or other agents) [Wooldridge and Jennings, 1995]. Trust assessment in multi-agent systems is essential for agents operating on behalf of humans in numerous domains. In e-commerce environments, such as eBay [eBay, 2007] or Amazon Marketplace [Amazon, 2007], agents acting on behalf of buyers must assess the trustworthiness of potential sellers to deliver purchased goods. Agents seeking recommendations via online referral networks like Epinions [Epinions, 2007] or Bizrate [Bizrate, 2007] must verify the accuracy of received referrals. For agents operating in online social networks, such as MySpace [MySpace, 2007], Friendster [Friendster, 2007], or LinkedIn [LinkedIn, 2007], trust assessment is necessary for identifying fake profiles, isolating online predators, and verifying the accuracy of information exchanged among "friends." Further, the multi-agent system paradigm provides a unique opportunity to simulate human interactions, providing direction for human decision-making in uncertain environments among potentially untrustworthy individuals.

Agents may use several techniques for building models of the trustworthiness of other agents, including social, "soft security" techniques (such as experiences and reputations) and more traditional, "hard security" mechanisms (such as credentials and passwords) [Barber, et al., 2003]. Soft security techniques are derived from human methods for assessing trustworthiness of other humans. In particular, this research addresses the relationship between two forms of social trust modeling: experience- and reputation-based trust modeling. A brief overview of both modeling types is given here. *Experience-based* trust modeling [Barber and Kim, 2002; Jonker and Treur, 1999; Schillo, et al., 2000] occurs when an agent uses the outcomes of its previous interactions with a partner to estimate that partner's future trustworthiness. Experience-based trust modeling is advantageous when agents have opportunities for numerous, repeated interactions. When the outcome of interactions are observable, transaction experiences provide an agent with trustworthiness feedback that is certain. Unfortunately, conducting the initial transactions used to build an experience-based trust models exposes a truster to risk if the truster has no other trust information available before conducting the transactions [Barber, et al., 2003].

In *reputation-based* trust modeling [Shi, et al., 2005; Teacy, et al., 2005; Yu and Singh, 2002], an agent builds its trust model of a potential transaction partner by requesting trust information, or reputations, from third-party agents. Adapted from the definition by Barber and Fullam, a *reputation* is a (not necessarily truthful) communication from one agent to another about the sender's trust in a third subject-agent [Barber and Fullam, 2003]. Reputation exchange is useful for quickly identifying trustworthiness characteristics of other agents [Mui, et al., 2002]. In systems with few opportunities for repeated transactions, rendering experience-based trust modeling infeasible, reputation exchange is an advantageous alternative.

Further, reputation exchange limits the risk exposure problem by providing an agent with trust information before conducting a first transaction. Agents entering a multi-agent system can quickly build trust models by requesting reputations from more knowledgeable agents. However, reputation-based trust modeling requires that at least some agents in the system have conducted—and observed the outcomes of—transactions with the agent whose trustworthiness is being modeled. Though an agent may assume its observations of transaction outcomes (the information used to build experience-based trust models) are certain, reputations (the information used to build reputation-based trust models) received from other agents introduce uncertainty, since reputation providers may be inaccurate or lying. Therefore, an agent has the additional task of assessing the accuracy of reputations it receives and the trustworthiness of the agents providing them.

Differences between experience- and reputation-based models mean each type of model conveys unique advantages and disadvantages. This research introduces Adaptive Trust Modeling, a technique enabling trusting agents to dynamically combine both experience- and reputation-based models to make accurate trust-related decisions under varied system conditions. Using Adaptive Trust Modeling, this research performs a quantitative analysis of the tradeoffs between experience- and reputation-based trust models, determining how environment factors (such as availability of experience opportunities, trustee trustworthiness dynamics, reputation accuracy, and reputation cost) influence which type of trust modeling is most useful. Further, this research devotes significant effort to assessing the cost-benefit tradeoff of reputation-based trust modeling when reputation acquisition incurs a cost; Adaptive Cost Selection is introduced, by which a trusting agent selects reputations to purchase based on analysis of individual reputation utility.

1.1 Problem

Clues about how to combine experience- and reputation-based trust modeling techniques are derived by examining how humans form and use trust models. Humans frequently, if informally, utilize trust information for decision-making. Humans may quickly identify the best type of trust modeling (experience-based vs reputation-based) for a situation, possibly combining both types. Consider the examples in Table 1-1 involving experience- and/or reputation-based trust modeling. These examples identify the types of factors influencing whether experience- vs. reputation-based modeling is appropriate for a given scenario.

Table 1-1. Examples in which humans make decisions regarding experience- vs. reputation-based trust modeling.

Example	Scenario
1	A traveler who has never been to New York seeks out several hotel recommendations before booking a Manhattan room online.
2	An elderly woman continues to schedule medical appointments with her doctor of thirty, trouble-free years, despite hearing negative referrals about the doctor from her neighbors.
3	Upon being asked to attend a critical, one-on-one meeting with the company's CEO, an employee queries coworkers for gossip about the CEO's mood and pet peeves.
4	A couple celebrating their 25th wedding anniversary wants to revisit their honeymoon hotel in Paris; they research numerous travel reviews before booking, since they suspect the hotel's quality may have changed since they visited last.
5	A young married couple decides not to seek the advice of a fee-only financial planner once they realize the planner's hourly charges are large compared to the value of the couple's financial portfolio.
6	A student, frustrated by the inaccuracy of daily weather forecasts on the morning news, stops watching the weather report, opting instead to base her outfit choices on how the weather appears from her window.
7	An investor's garrulous brother-in-law repeatedly gives the wrong advice about which stocks to purchase; the investor begins purchasing stocks according to the opposite of his brother-in-law's advice.

From Table 1-1, several qualitative, intuitive guidelines for using experience- vs. reputation-based modeling emerge. These guidelines are described in Table 1-2 by four environment factors that influence the choice of model type (experience- vs. reputation-based): 1) availability of experience opportunities, 2) trustee trustworthiness dynamics, 3) reputation accuracy, and 4) reputation cost. A truster should base trust decisions on experience-based models only when the truster has sufficient experience opportunities with the potential trustee. Similarly, the truster cannot rely on experience-based models if the potential trustee's behavior is too untrustworthy or dynamic for the truster to model using experiences. On the other hand, the truster can rely on reputation-based models if the provided reputations are accurate and inexpensive. Table 1-3 identifies the environment factor influencing the choice of model type for each of the examples introduced in Table 1-1.

Table 1-2. Environment factors influencing choice of trust modeling type (experience- vs. reputation-based), with conditions under which each type of modeling is favored.

Environment Factor Influencing Choice of Model Type	Use Experience-Based Trust Modeling	Use Reputation-Based Trust Modeling
Availability of Experience Opportunities	*Sufficient* experience with potential trustee	*Insufficient* experience with potential trustee
Trustee Trustworthiness Dynamics	Trustee trustworthiness pattern changes *infrequently*	Trustee trustworthiness pattern changes *frequently*
Reputation Accuracy	Reputations are *inaccurate*	Reputations are *accurate*
Reputation Cost	Reputations are *expensive*	Reputations are *inexpensive*

Table 1-3. Examples in which humans make decisions regarding experience- vs. reputation-based trust modeling. Each example is labeled with the environment factor influencing the human's choice of trust modeling type.

Example	Scenario	Environment Factor Influencing Choice of Model Type
1	A traveler who has never been to New York seeks out several hotel recommendations before booking a Manhattan room online.	Availability of Experience Opportunities
2	An elderly woman continues to schedule medical appointments with her doctor of thirty, trouble-free years, despite hearing negative referrals about the doctor from her neighbors.	Availability of Experience Opportunities
3	Upon being asked to attend a critical, one-on-one meeting with the company's CEO, an employee queries coworkers for gossip about the CEO's mood and pet peeves.	Availability of Experience Opportunities
4	A couple celebrating their 25th wedding anniversary wants to revisit their honeymoon hotel in Paris; they research numerous travel reviews before booking, since they suspect the hotel's quality may have changed since they visited last.	Trustee Trustworthiness Dynamics
5	A young married couple decides not to seek the advice of a fee-only financial planner once they realize the planner's hourly charges are large compared to the value of the couple's financial portfolio.	Reputation Cost
6	A student, frustrated by the inaccuracy of daily weather forecasts on the morning news, stops watching the weather report, opting instead to base her outfit choices on how the weather appears from her window.	Reputation Accuracy
7	An investor's garrulous brother-in-law repeatedly gives the wrong advice about which stocks to purchase; the investor begins purchasing stocks according to the opposite of his brother-in-law's advice.	Reputation Accuracy

Despite the clues human behaviors give for determining when to use experience- vs. reputation-based modeling, humans often make mistakes when assessing trustworthiness. Trust assessment mistakes may be caused by irrationality; for example, a customer may continue to trust a service-provider—long after recommendations have shown the service-provider to be a crook—because the customer refuses to acknowledge his previous poor decisions to trust the service-provider. In addition, trust assessment mistakes may be related to human emotion, as is the case when an infatuated individual is taken advantage of by a lover who happens to be a con artist. Trust assessment mistakes may be due to poor association between current observations and previous experiences. For example, a wary store owner might deny service to a poorly-dressed customer because the owner expects the customer will shoplift (the store owner associates poor dressing habits with shoplifters). Similarly, an unsuspecting homeowner may answer the door when an intruder knocks if the intruder dresses convincingly as a delivery person (the homeowner associates delivery uniforms with trustworthy individuals). For humans, trust assessment is further complicated by social constraints; laws prevent individuals from discriminating based on race or ethnicity, and, in some circles, it is socially or ethically unacceptable to gain reputation information through gossip. Human trusters benefit significantly from the Adaptive Trust Modeling technique presented in the research, an objective trust evaluation technique which weighs the utility of both experience- and reputation-based models to produce the most accurate trust assessment possible.

Humans often also have difficulty gauging the value of trust information, investing too much or too little to build a trust model relative the magnitude of the decision at stake. For example, a prospective vacationer may spend numerous hours scouring tourism review websites to determine the best hotel to patronize, though the value of the hours spent researching significantly outweighs the cost of the hotel room. Conversely, a consumer looking to purchase an automobile may purchase an attractive red convertible in a spur-of-the-moment decision before acquiring significant data about the vehicle's reliability. Adaptive Cost Selection enables trusters to objectively assess the value of trust information to determine how much trust information to acquire based on the magnitude of the transaction decision in question and the information's expected benefit.

Lastly, because the guidelines in Table 1-2 are vague (specific words causing ambiguity are italicized in Table 1-2), a truster has difficulty answering questions such as:

- When is the availability of experience opportunities *sufficient* enough to rely on an experience-based model?

- How *frequently* may a trustee change its behavior pattern yet still be accurately modeled by experiences?
- How *accurate* must provided reputations be to make reputation-based modeling advantageous?
- At what point do reputations become too *expensive* to make reputation-based modeling feasible?

The purpose of this research is to quantitatively identify the tradeoffs between experience- and reputation-based trust modeling by answering the questions above. This research introduces the Adaptive Trust Modeling technique to identify under which circumstances (according to the factors in Table 1-2) experience- vs. reputation-based trust modeling is preferable, combining both models for greatest accuracy in trust-based decision-making. In particular, assessing the value of trust information (including acceptable expense of reputations) is difficult; the connection must be established between the accuracy of one piece of trust information and the payoff from a truster's resulting decision, based on the aggregation of all available trust information. This research presents the Adaptive Cost Selection algorithm, which selects reputations to purchase, weighing the cost of each reputation against the resulting decision accuracy that reputation produces.

1.2 Research Questions

This research examines the following hypothesis:

Experience- and reputation-based trust models can be integrated to yield an aggregate trust model more accurate and cost-effective than either single model.

Experience-based and reputation-based trust modeling are each suited to different trusting scenarios, based on environment factors such as the availability of experience opportunities, trustee trustworthiness dynamics, accuracy of available reputation providers, and cost to acquire reputations. In some multi-agent systems, a truster benefits from using both experience- and reputation-based models in assessing the trustworthiness of potential trustees. Therefore, a truster must determine what type of trust information—whether from experiences or reputations—are best suited for given system conditions. If the truster decides that both types of trust information are useful, the truster must have a technique for combining the two trust model types, determining whether one model is more valuable than the other. While other research emphasizes use of experience-based modeling only [Jonker and Treur, 1999; Schillo, et al., 2000], reputation-based modeling only [Shi, et al., 2005; Yolum and Singh, 2003], or static hybrids [Barber and Kim, 2002; Huynh, et al., 2004; Ramchurn, et al., 2004], this research introduces Adaptive Trust Modeling, a tool to dynamically determine the best combination of experience- and reputation-based trust modeling, identifying the best type of trust modeling for given system conditions. In following with this goal, the research will seek to answer the following two research questions:

> *RQ 1: How do characteristics of a truster's environment affect the usefulness of the truster's experience- and reputation-based models?*
>
> *RQ 2: How should a truster assess the value of trust information (specifically, reputations), in light of the cost of that information, to determine what trust information to acquire?*

The following subsections expand upon these research questions.

1.2.1 Research Question 1: Environment Characteristics Influencing Experience- and Reputation-Based Models

Research Question 1 asks: *How do characteristics of a truster's environment affect the usefulness of the truster's experience- and reputation-based models?* A truster's environment can vary, affecting which type of trust model, experience- vs. reputation-based, is more advantageous. A truster must know what combination of trust modeling techniques to exploit for given system conditions. Toward the goal of identifying how environment factors influence the usefulness of a truster's experience and reputation-based model, this research question yields two sub-questions:

RQ 1.1: *How do characteristics of a truster's environment affect the usefulness of the truster's experience-based models?*

Experience-based models have unique qualities that differentiate them from reputation-based models: experience-based models are built up over numerous interactions, and the data points (outcomes of those interactions) are usually observed by the truster with certainty. Further, experience-based models require frequent additional interactions experiences over time to identify changes in a trustee's trustworthiness behavior. Therefore, this research examines how the following environment factors impact the usefulness of a truster's experience-based models:

1) Availability of experience opportunities and
2) Trustee trustworthiness dynamics.

The availability of experience opportunities influences the accuracy and certainty of the truster's experience-based model. As a truster accumulates more experiences with a trustee, the truster develops a more accurate experience-based model of the trustee's trustworthiness. As a result, the truster's reputation-based model may be favored early on, when the truster has observed no or few experiences. However, as more observations are accumulated, the truster should increase its reliance on its experience-based model.

The trustworthiness of a potential trustee influences a truster's ability to build an experience-based trust model about that trustee. First, if a trustee tends to be untrustworthy, the truster will be less likely to conduct transactions with the trustee. Therefore, the truster will take longer to accumulate transaction observations upon which to build its experience-based model. As a result, the truster should utilize a reputation- over experience-based model. Additionally, the truster may need to implement some form of "exploration," occasionally risking an untrustworthy transaction to observe additional transactions, especially if the trustee may have changed its behavior to become more trustworthy. On the contrary, when a trustee tends to be trustworthy, the truster should quickly accumulate transaction observations upon which to build an experience-based model. In this case, the experience-based model should more quickly overtake a reputation-based model in terms of accuracy.

The frequency with which a trustee changes its level of trustworthiness, or behavior pattern, also influences the truster's ability to build an experience-based trust model. If the trustee changes its behavior pattern frequently and continuously, the truster will not accumulate enough transaction observations to build an experience-based model with accuracy. In this case, the truster is more likely to rely on a reputation-based trust model. However, if the trustee maintains a consistent behavior pattern, the truster will build an experience-based model with increasing certainty as additional transaction observations are accumulated, thereby decreasing its reliance on reputation-based trust modeling.

The purpose of this research question is to quantitatively assess the effects of environment factors (availability of experience opportunities and trustee trustworthiness dynamics) on the usefulness of a truster's experience-based trust model. This research question is addressed in Section 3.2.

RQ 1.2: *How do characteristics of a truster's environment affect the usefulness of the truster's reputation-based models?*

Reputation-based models have unique characteristics because reputations are communicated from third-party reputation providers. The truster lacks certainty as to the accuracy of the reputations, since providers may be incompetent or may choose to lie. Further, the truster may have access to several potential reputation providers; the truster must choose how many reputations to acquire, which providers to utilize, and how to combine the acquired reputations to achieve the most accurate aggregation possible. Finally, acquisition of reputations may cost a truster in terms of purchase prices, time, and communication costs. Therefore, this research examines how the following environment factors impact the usefulness of a truster's reputation-based models:

1) Reputation accuracy and
2) Reputation cost.

When reputations are accurate, they provide valuable predictions of transaction outcomes, and a truster will rely on its reputation-based model over its experience-based model. More specifically, when reputations are more accurate, the truster must accumulate more transaction observations (build a more accurate experience-based model) before it will stop favoring its reputation-based model. On the contrary, when reputations are inaccurate, only a few transaction observations are needed to build an experience-based model with accuracy exceeding that of the reputation-based model.

The error consistency of reputations, in addition to accuracy, plays an important role in determining a truster's reliance on its reputation-based model. Reputations with highly-consistent error, though inaccurate, may still provide useful information to the truster. The consistency of the reputation provider's error gives the information receiver a transformation by which to correct the information's inaccuracy. Therefore, inaccurate reputations with highly-consistent error may cause a truster to favor its reputation-based trust model, even though it has built up an accurate experience-based model.

The availability of multiple reputations from many providers introduces a problem of combining reputations of varying accuracy into an aggregated reputation-based model. A truster must determine the number of reputations to consider and how to combine those reputations to achieve the most accurate aggregation possible. Further, when the acquisition of each reputation incurs a cost, the truster must evaluate the tradeoff between that cost and the benefit of increased accuracy the reputation provides to the truster's reputation-based model. Since this cost-benefit evaluation of reputations is a difficult problem, it is addressed separately in Research Question 2.

The purpose of this research question is to quantitatively assess the effects of environment factors (number and accuracy of available reputation providers, and cost to purchase reputations) on the usefulness of a truster's reputation-based trust model. This research question is addressed in Section 3.3.

1.2.2 Research Question 2: Assessing Trust Information Value

Research Question 2 asks: *How should a truster assess the value of trust information (specifically, reputations), in light of the cost of that information, to determine what trust information to acquire?* It cannot always be assumed that trust information is free. Instead, trust information, especially reputations, often incurs costs related to acquisition time and communication or fees charged by providers for specialized information. For example, employment recruiters charge companies for providing qualified candidates. Travel guidebooks, which discuss the reputations of tourism-related businesses such as hotels and restaurants, are sold for a price. Even access to internet-based consumer product rating magazines requires a paid subscription, in many cases.

The cost of acquiring reputations from providers influences the accuracy of a truster's reputation-based model, and, therefore, the truster's tendency to favor its reputation- over experience-based model. When reputation costs are high, the truster is more likely to restrict the number of reputations it acquires. As a result, the accuracy of its reputation-based model may be low, and the truster may be more inclined to rely on its experience-based model. On the contrary, when reputation costs are low, the truster is less likely to be restricted by reputation costs; the truster's ability to acquire more reputations means the truster can achieve a reputation-based model of higher accuracy. Therefore, if the truster builds a highly-accurate reputation-based model because reputation costs are low, the truster may be more inclined to rely on its reputation- over experience-based model. Further, if a truster knows the value of a reputation, the truster can determine the price it is willing to pay for that reputation (or which reputations it should purchase given a fixed reputation cost).

Assessing the value of (or, the cost a truster should be willing to pay for) reputations is a difficult problem. The truster must evaluate the contribution—in monetary terms—of reputations toward the truster's payoff from a given transaction. In addition, the value of a single reputation must be isolated from that of other reputations contributing to the truster's decision. Assessing reputation value is further complicated by the fact that specific transaction payoffs are dependent on trustee decisions, which the truster cannot control. A reputation may correctly indicate the truster should trust (resulting in a positive payoff) in one case, or correctly indicate the truster should not trust (resulting in zero payoff) in another; though the reputation gives a correct assessment in both cases, the truster's payoff in the two cases is very different.

Though this research question focuses on valuating reputations in light of reputation cost, it should be noted that experience-based trust information has value, also. Though time to conduct the transaction and possible losses incurred while experiencing the transaction are considered part of a transaction's cost, they can also be considered an investment in building up an experience-based model that remains useful beyond the single transaction. Therefore, if the value of experience-based trust information can be assessed (in the same way the value of reputation-based trust information is assessed), the truster can determine the utility of intentionally investing time and risk to build an experience-based model.

The purpose of this research question is to address the cost-benefit tradeoff of purchasing trust information—in particular, reputations—enabling a truster to select the appropriate combination of reputations to purchase as a function of number of reputation providers, estimated accuracy of reputations, and estimated reward from acquiring them. This research question is addressed in Chapter 4.

1.3 Research Objectives

The encapsulating purpose of the research is to identify how trusters may utilize both experience- and reputation-based trust modeling to achieve more accurate decision-making tools than using either modeling technique alone. Toward this goal, the research aims to achieve three concrete objectives:

1) An Adaptive Trust Modeling technique for weighting experience- vs. reputation-based models to produce the most accurate and cost-effective aggregated model possible,
2) A quantitative analysis of the tradeoffs between experience- and reputation-based models to determine the conditions under which each type of model is favorable, and
3) An Adaptive Cost Selection algorithm for assessing the value of trust information, enabling a truster to determine what information to acquire when cost is a factor.

First the research provides a weighting technique called Adaptive Trust Modeling, based on error estimates of both experience- and reputation-based models, to integrate suggestions from each model about whether to trust. Adaptive Trust Modeling also predicts the error (certainty) of the aggregate model. Further, an extension of Adaptive Trust Modeling permits the aggregation of trust information from more than two sources, as in scenarios in which reputations from numerous reputation providers must be combined. Weighting is dynamic, taking into consideration changing factors influencing the accuracy of each type of trust model, including 1) availability of experiences, 2) trustee trustworthiness dynamics, 3) number and accuracy of available reputation providers, and 4) cost to acquire reputations.

Second, the research performs a quantitative investigation to identify how each of these four factors influences a truster's tendency to rely on experience- vs. reputation-based trust models. The research identifies a theoretical relationship between the number of transactions a truster observes and the resulting accuracy of its experience-based trust model. Next, the research identifies how a potential trustee's trustworthiness (trustworthy vs. untrustworthy) and dynamics in the trustee's behavior affect the truster's experience-based model (by influencing the availability of interactions the truster observes). The research identifies a relationship between the accuracy of a reputation-based model and its weighting, as compared to an experience-based model, as the experience-based model is built over time. This research introduces a technique called Error-Sensitive Translation, which makes use of inaccurate reputations from providers with consistent error.

Finally, the research introduces the Adaptive Cost Selection algorithm for valuating trust information. When there is a cost to purchase reputations, the research theoretically assesses the tradeoff between the amount paid for reputations and resulting increase in profit resulting from better accuracy in trust-based decisions. The research enables trusters to computationally maximize decision-making accuracy by utilizing both experiences and reputations.

1.4 Contribution

This research delivers 1) the Adaptive Trust Modeling tool for producing accurate aggregated trust models by weighting experiences and reputations, 2) a quantitative assessment of the conditions under which each type of model is favorable, and 3) the Adaptive Cost Selection algorithm for valuating trust information. The implications of these research products are wide-reaching, both for agent and human trusters.

Existing agent trust research limits an agent to experience-only [Jonker and Treur, 1999; Schillo, et al., 2000], reputation-only [Huynh, et al., 2005; Yolum and Singh, 2003], or static hybrid trust models (excluding "hard security" mechanisms, such as credentials, passwords, and encryption). Few examples of static hybrids exist; work by Barber and Kim simply averages the results of both models, regardless of system variables [Barber and Kim, 2003], while work by Patel, et al., utilizes reputations only if no experience-based model exists [Patel, et al., 2005]. In each limiting case, a human designer must estimate the best type of trust modeling for the given multi-agent system, equipping agent trusters with the trust modeling capabilities the designer deems most suitable. In some situations, the single best type of trust modeling may be unclear. In others, inflexible agent trusters are ill-equipped to model trust appropriately in the midst of changing system conditions based on availability of experience opportunities, trustee trustworthiness dynamics, reputation availability and accuracy, and reputation cost.

In contrast, Adaptive Trust Modeling enables an agent truster to dynamically and automatically adapt its reliance on experience- or reputation-based trust as system conditions vary. For example, agent trusters may initially rely on reputations in a large multi-agent system with few experience opportunities; however, as sub-communities form, in which more repeated experience opportunities are available, trusters may increase their dependence on experience-based trust modeling. Similarly, an agent truster who relies on inexpensive reputations may instead place more weight on a tentative experience-based model if the cost of purchasing reputations increases dramatically. Adaptive Trust Modeling enables agent trusters to transition smoothly along the spectrum of experience- and reputation-based trust model usage by translating these system conditions into influencers of trust model accuracy.

In many domains, humans perform their own trust-based decision-making, which is susceptible to irrationality and incorrect judgments about the correct combination of trust modeling techniques to use. For example, a home improvement "do-it-yourselfer" may misjudge the level of project difficulty he can handle without guidance, often overestimating his level of experience while discounting the expertise of professionals. In online social networks such as MySpace and Friendster, teenagers may make unwise trusting decisions, risking personal safety to achieve popularity and large circles of "friends." Similarly, business professionals using networking sites like LinkedIn, in job search desperation, may be scammed by false job leads or, in a quest for reciprocal recommendations, risk promoting untrustworthy acquaintances. In the Freecycle email group system [Freecycle, 2007], by which local members exchange free items, offerors may be frustrated by requesters who fail to pick up items as promised, and eventually develop smaller trusted subgroups with whom they exchange. In each example, system conditions—such as availability of experience opportunities, trustee trustworthiness dynamics, and accuracy and cost of reputations—may change. The social networks described here are best maneuvered using both reputation-based modeling (for identifying strangers within the larger system of participants) and experience-based modeling (for maintaining personal contacts in sub-communities). Adaptive Trust Modeling quantitatively computes the tradeoffs between experience- and reputation-based modeling, automating trust assessment to take advantage of both modeling types for the human user or software agent.

By quantitatively analyzing the system conditions under which experience- vs. reputation-based models are advantageous, this research provides human trusters with intuitive explanations for when each type of trust modeling, experience- and reputation-based, is most appropriate. The theory and experimental results clarify some common misconceptions, including:

> <u>Misconception 1</u>*: Large systems (with many trusters/trustees) always make experience-based modeling ineffective.* In truth, experience-based modeling is effective as long as a truster has numerous, repeated opportunities to interact with each trustee it considers. Experience-based modeling in large systems is perceived to be ineffective because trusters do not always conduct the large volume of interactions necessary to make experience-based modeling of each potential trustee effective in such scenarios. However, trusters who conduct large numbers of transactions in large systems may find experience-based modeling useful; conversely, trusters who very rarely conduct any transactions, even in small systems, may have inaccurate experience-based models (see Section 3.2.1 Availability of Transaction Observation Opportunities).
>
> <u>Misconception 2</u>*: Infrequent transactions always make experience-based modeling ineffective.* In truth, experience-based modeling is effective as long as the frequency with which experience observations are accumulated sufficiently exceeds the frequency with which a trustee changes its trustworthiness behavior pattern. Infrequent interactions still build an effective experience-based model when trustee behavior patterns change rarely or never. Conversely, experience-based trust modeling may be ineffective if a trustee changes its trustworthiness behavior pattern very frequently, even if the truster conducts frequent (yet not

sufficiently frequent) interactions with the trustee (see Section 3.2.3 Dynamic Trustee Trustworthiness).

Misconception 3: *Inaccurate reputation providers are never useful.* In truth, if a reputation provider produces reputations that, though inaccurate, have consistent error, the truster can perform transformations (determined by error magnitude) on those reputations to achieve useful information about a trustee (see Section 3.3.1.2 Performing Error-Sensitive Translation: Overcoming Mean Errors).

Misconception 4: *A truster can rely on experience-based modeling for low-value transactions, but should always acquire reputations when considering high-value transactions.* This misconception arises from the idea that reputations are a more accurate supplement to a truster's existing experience-based model, which is not always true. In truth, though a truster's experience-based model may be considered "free" and reputations may incur a cost, a truster's decision to utilize experience vs. reputations must be based on the relative accuracy of both models, as well as the cost of reputations relative to the benefit of interacting with the trustee. If the truster's experience-based model is more accurate than the reputations it has access to, the truster should rely more on experience than on reputations. If the benefit of the potential interaction is low relative to reputation cost, the truster may choose to rely on experience, or, if no experience-based model exists, on no model at all (see Section 3.3.1 Reputation-Based Model Accuracy and Section 3.3.2 Reputation Cost).

Misconception 5: *A truster should always acquire only the single or few "best" reputations.* In truth, when reputations are free to acquire, a truster achieves the lowest predicted error by aggregating as many reputations as possible, weighting each according to estimated error (see Section 3.3.2 Reputation Cost).

Misconception 6: *A truster should always rely on reputation-based modeling when it has no experience with a trustee.* In truth, if reputations incur a prohibitive cost, a truster may be better off relying on no trust model at all. If no trust information is available, the truster must decide whether the risk posed by the transaction's magnitude is worthwhile (see Section 4.1.5 Assessing Risk via *AverageReward* Functions).

Analysis of experience- and reputation-encouraging system conditions improves strategic trust-related decision-making. If a truster has control over building its experience- and reputation-based models, knowing the system conditions conducive to each type of model instructs the truster about which type of model to invest in building. For example, if a truster knows reputations are expensive or inaccurate, it might seek out more opportunities for experiences, knowing that each experience is an investment that provides useful trust information for future trust decisions. Or, if that truster realizes experience opportunities are rare, it may put extra effort into seeking out additional reputations that are cheaper or more accurate. Further, an individual who benefits from a specific type of trust modeling may seek out (or even influence) specific system conditions to encourage its preferred trust modeling technique. For example, reputation brokers might search for niche markets for reputations by looking for systems in which numerous, repeated transactions are rare. Those same brokers might reduce reputation costs or increase reputation accuracy, with the goal of increasing system-wide reputation-based modeling. Finally, if a truster requires a certain level of accuracy in its trust assessments, Adaptive Trust Modeling informs the truster of the quantity and cost of trust information required, motivating the truster to obtain the needed trust information.

Finally, Adaptive Cost Selection enables a truster to assess the value of trust information. By knowing the worth of a given piece of trust information, a truster can decide how much time, effort, and money it is willing to invest to acquire that information. Further, Adaptive Cost Selection assists both reputation providers in setting reputation costs and trusters in negotiating reputation costs (when those costs are flexible).

This research produces tools to aid both human and agent decision-makers in determining when to trust. Adaptive Trust Modeling enables trusters to weight experience- and reputation-based models, yielding accurate and cost-effective aggregated models. A quantitative analysis of the tradeoffs between experience- and reputation-based models eliminates misconceptions about both model types and empowers agents to make trust-related decisions to acquire the types of trust information they can utilize best. Adaptive Cost Selection assesses the value of trust information, enabling a truster to analyze the cost vs. benefit of acquiring trust information.

Chapter 2
BACKGROUND

Trust assessment has numerous applications to real-world domains, including business transactions [Yamagishi and Matsuda, 2003], e-commerce [eBay, 2007; Amazon, 2007], referral networks [Epinions, 2007; Bizrate, 2007], and online social networks [MySpace, 2007; Friendster, 2007; LinkedIn, 2007]. The large range of these potential applications justifies the value of trust models based on both experience and reputations. The related work discussed in this chapter first presents common definitions of trust and representations for trust models (Section 2.1). Second, the bases of human trusting are described as a foundation for agent-based trust technologies designed to both assist humans and operate alone in multi-agent systems (Section 2.2). Next, recent research progress related to experience-and reputation-based trust modeling is outlined (Section 2.3). Finally, the contributions of this research to the state of the art are delineated (Section 2.4).

2.1 Defining Trust

Definitions of the terms "trust" and "reputation" vary widely. Jurca and Faltings describe reputation in general terms as "information about [an agent's] past behavior" [Jurca and Faltings, 2002]. Barber and Kim, describing trust in information domains, closely link trust in an information provider ("confidence in the ability and intention of an information source to deliver correct information") to the information provider's reputation ("the amount of trust an information source has created for itself through interactions with other agents") [Barber and Kim, 2003]. Others, such as Yu and Singh, identify trust with the perspective of a single agent, while reputation is considered a group opinion [Yu and Singh, 2002]. As defined by Sztompka, "trust is a bet on the future contingent actions of others" [Sztompka, 1999]. Further, from the definition given by Barber and Fullam, reputation is considered to be a truster agent's subjective estimate of the trust a set of agents has in a trustee, denoted by $r_{s,a}^{G}$, where s is the subject-agent (trustee) whose trust is being modeled, G is the set of agents whose trust in s is being modeled, and *a* is the agent who is modeling the trust of *G* in *s* [Barber and Fullam, 2003].

Trust may be considered to have numerous facets. Falcone, et al., have proposed a method for evaluating trust from beliefs about several factors [Falcone, et al., 2002]. Causal factors of trust in an agent may include the agent's intent, or tendency toward honest behavior (in the negative sense, an agent's tendency toward malice). Examples of honest behavior include an agent providing information it believes to be truthful, or an agent attempting to follow through with an action it has agreed to perform. An agent's competence, or raw ability to accomplish a task, such as providing accurate information or performing a desired action, is another important factor. According to Falcone, et al., trust can also be based on availability (an agent's freedom from commitments which limit its ability to accomplish a task for a potential cooperative partner), promptness (the speed at which an agent responds to task requests by accomplishing the agreed upon task), or external factors (an agent's susceptibility to uncontrollable factors affecting the agent's ability to accomplish an agreed upon task). Exposure to external factors may vary from agent to agent depending on the agent's methods for completing the desired task, and so, in some cases, may be related to the agent's competence [Falcone, et al., 2002]. Gefen emphasizes a distilled list of fewer trust facets, including competence, benevolence, and integrity [Gefen, 2002]. Barber et al. examine two facets: intent (honest vs. malicious) and competence (high vs. low). They argue that, in many cases, knowing the reason for trustworthiness failure (malicious intent or incompetence) is immaterial to the truster, who may suffer the same consequence regardless of cause [Barber, et al., 2003]; Fullam and Barber use the term "reliability" to encapsulate both intent and competence aspects of trust [Fullam and Barber, 2004].

Trust may be transitive; in other words, if agent A trusts agent B, and agent B trusts agent C, then agent A will most likely trust C. However, work by Gray, et al., Guha and Kumar, and Jøsang, et al., examining the propagation of trust in networks, has shown that trust is not completely transitive. Rather, trust degrades as chains of inter-agent relationships lengthen [Gray, et al., 2003; Guha and Kumar, 2004; Jøsang, et al., 2003]. In addition, trust may be asymmetric; one agent's trust in a second agent does not ensure the second agent's trust in the first agent [Hardin, 2002]. Further, trust may be multidimensional. Gujral, et al., describe multi-dimensional trust, in which agents exhibit different levels of trustworthiness according to different metrics (quality of product delivered or timeliness of delivery, for example) [Gujral, et al., 2006]. Work by Griffiths includes the additional dimensions of success (likelihood of successful execution) and cost [Griffiths, 2005].

This research relies on the definition of trust provided by Sztompka ("trust is a bet on the future contingent actions of others" [Sztompka, 1999]). Further, this research adopts a definition of reputation adapted from Barber and Fullam: a reputation is a (not necessarily truthful) communication from one agent to another about the sender's trust in a third subject-agent [Barber and Fullam, 2003].

2.2 Trust in Human Societies

It is valuable to begin a study of trust by examining trust among humans. Humans utilize trust often, if informally. Therefore, observing successful trust in human social contexts provides indicators of suitable agent-based trust strategies. Scrutinizing human error in trusting is equally as valuable, providing insight for agent-based tools robust to those human mistakes. As a result this research yields both 1) tools for assisting human trusters and 2) successful navigation of trusting scenarios by software agents in multi-agent systems.

Human exposure to trusting dynamics begins in infancy, when babies learn to rely on parents for basic needs [Weigert, 1962]. Experiments by Ainsworth demonstrate that a child's tendency to trust is directly correlated to the sensitivity of his caregiver toward accommodating those needs [Ainsworth, 1979]. A child raised in a nurturing, even sheltered environment may later approach new situations with naïve super-trusting, while a child whose upbringing is plagued by abuse may develop habits of extreme distrust [Worchel and Austin, 1986], even to the point of abnormalities such as Reactive Attachment Disorder [Hanson and Spratt, 2000]. Research has even detected a biological link between hormone levels and an individual's inclination to trust [Kirsch, et al., 2005].

According to Wrightsman's Philosophies of Human Nature Scale, humans base decisions to trust on assumptions about others in relation to several factors, including altruism, trustworthiness, and rationality [Wrightsman, 1974], perhaps related to a greater instilled worldview. Work by Rotter demonstrates that humans develop expectations, based on interactions in numerous relationships, which provide the basis for inferences about future interactions with unknown individuals [Rotter, 1954]. From this perspective, trust may be said to be association-based. Trivers shows how reciprocal altruism develops among humans—and animals—as a means of self-preservation; by two individuals relying on each other, the chances of survival for each increases [Trivers, 1971]. Further, Bennis argues that two individuals will tentatively expose themselves to small amounts of risk; if an exposure is met by the other's acceptance, exchange continues and trust is built up over time [Bennis, et al., 1964]. This type of mutual exchange trust-building is a form of experience-based trust modeling (discussed in Section 2.3.1), in which a truster builds its estimate of a trustee's trustworthiness characteristics based on numerous, repeated interactions.

In one-on-one relationships, humans often have "signs" which provide clues about the trustworthiness of a potential trustee. Bacharach and Gambetta name these observable properties *manifesta*, indications of unobservable trustworthiness properties called *krypta* [Bacharach and Gambetta, 2001]. According to their work, untrustworthy individuals mislead trusters by imitating the manifesta of a truly trustworthy individual. Using the example of taxi drivers, who make numerous trust decisions every day regarding strangers, Gambetta and Hamill explain that drivers look for reliable signs that are difficult for criminals to fake (related to appearance, location, etc.) when selecting cab hailers [Gambetta and Hamill, 2005].

Humans also use reputation information from third parties when making trust decisions, communicating reputations either one-to-one or by broadcast. According to Nicholson, humans use gossip (a form of one-to-one reputation exchange) for networking, influence, and social alliances [Nicholson, 2001]. One-to-one reputation exchange permits reputation providers to communicate different reputations to different reputation receivers, creating unique opportunities for deception. Humans utilize broadcast reputations in online applications, such as eBay, Amazon, and Epinions, where reputation information is posted publicly for all users. Applications such as Yahoo

Groups [Yahoo, 2007] employ both types of reputation acquisition; reputation providers may respond to reputation requests either publicly to the entire group or privately to the requester.

The downside of human trust-based decision-making is human tendencies toward making mistakes in trustworthiness assessment. Humans may be inclined to continue trusting an untrustworthy individual for several reasons. Weber and Carter describe the pressure to trust based on "social structure" [Weber and Carter, 2003]; for example, a mother will continue to lend money to her irresponsible adult son "because he's family." Similarly, an infatuated teenager will remain faithful to a cheating lover, simply because of emotional attachment. Upon receiving new evidence about a trustee's cheating tendencies (perhaps through recommendations from friends), a truster may respond with denial. Gardenfors addresses the need for individuals to revise beliefs since "people accept as certain things that really aren't because of prejudice, faulty inferences, or trusting too many authorities" [Gardenfors, 1988]. Further, trusters are susceptible to miscorrelating observations (manifesta) and resulting inferences about trustworthiness characteristics (krypta) [Bacharach and Gambetta, 2001], as when a taxi driver refuses an innocent hailer because of the hailer's questionable appearance. Individuals in online social networks such as MySpace may disregard commonsense precautions in a quest for increased popularity, exposing themselves to criminals [Apuzzo, 2006]. The Adaptive Trust Modeling and Adaptive Cost Selection techniques proposed by this research aid both human and software agent trusters in avoiding these trust-based decision-making errors.

2.3 Modeling Trustworthiness

Agents—whether human or software—must model both the worth and risk of interacting with other agents in order to evaluate whether to cooperate and ultimately to provide a decision basis for whom to trust [Marsh, 1992]. Trust models serve as decision criteria for whether to cooperate with the agent whose trust is being modeled. As summarized from Fullam et al., a truster's models of trustee trustworthiness should have several characteristics [Fullam, et al., 2005a]. First, trust models must be accurate predictors of the trustee's future behavior [Fullam, 2003; Klos and LaPoutre, 2004;

Whitby, et al., 2004]. Second, trust models must be adaptive, changing to accommodate dynamic trustworthiness characteristics of trustees who might suddenly lose competence or maliciously employ strategies to vary trustworthiness [Fullam and Barber, 2005]. In addition, trust modeling algorithms must quickly create usable new models when unknown agents enter the system. Quick trust model bootstrapping is necessary to thwart trustees attempting to change identities by repeatedly entering and leaving a system, and can be assessed by the time to converge to sufficiently accurate models [Ding, et al., 2004].

A truster must effectively translate its trust models to make decisions and take actions. Given a potential transaction (with implicit or explicit agreement or terms), a truster must correctly decide whether to participate in the agreement, predicting whether the agreement will be fulfilled by the trustee [Falcone, et al., 2004; Schillo, et al., 2000]. Further, a truster must estimate the utility of an interaction, or degree to which the agreement will be fulfilled, to better negotiate terms of the agreement, such as appropriate payment [Neville and Pitt, 2004]. Finally, trusters must identify—and collectively isolate—untrustworthy trustees by refusing to interact with them [Barber and Kim, 2002; Biswas, et al., 1999].

Agents can perform trust assessment via traditional security techniques (such as credentials or passwords) or "soft security" methods (social trust modeling techniques based on past experiences or reputations provided by other agents) [Artz and Gil, 2007]. Section 2.3.1 discusses the advantages of soft security techniques over traditional security techniques, while Section 2.3.2 and Section 2.3.3 explain experience-based trust modeling and reputation-based trust modeling, respectively. This section demonstrates that both experience- and reputation-based modeling techniques have strengths and weaknesses, motivating this research to deliver techniques for combining both modeling types to yield robust, aggregate trust models.

2.3.1 TRADITIONAL SECURITY TECHNIQUES VS. "SOFT SECURITY"

Traditional security methods (dubbed "hard security" by Rasmusson and Jansson [Rasmusson and Jansson, 1996]) include techniques such as credentials, passwords, firewalls, and encryption. Bacharach and Gambetta, discussing trust based on appearances, present the weaknesses of human use of informal credentials in social interaction [Bacharach and Gambetta, 2001]. Often humans trust based on the appearance of a potential trustee ("The man *looks* like a policeman, so he must *be* a policeman"). However, appearance-based trust is often unreliable, since appearances may be falsified, and may be hard to obtain if visual contact cannot be established.

Hard security techniques in software applications are designed to serve as barriers, preventing untrustworthy entities from entering systems or accessing information. Hard security mechanisms are relatively easy to establish: commercial software and hardware are readily available for building firewall and password-protected fences around sensitive information and networks. However, while hard security techniques are widely used, and successful in many cases, for applications such as personal computer protection and e-mail access restriction, they provide an "all-or-nothing" approach. Hard security techniques are unable to protect against untrusted entities that break through the hard security mechanism, for example, by producing a false credential, circumventing a password, bypassing a firewall, or breaking encryption [Barber and Kim, 2003].

Wong and Sycara utilize credentials in the Retsina model, enabling agents to prove their identities by ensuring agents are uniquely identifiable and bound to a human with a public key certificate [Wong and Sycara, 2000]. Poggi, et al., present certificate-based permissions protocols for the JADE platform [Poggi, et al., 2003]. Work in biometrics has produce technology for hard-to-falsify personal credentials for humans [Bechelli, et al., 2002; Wilson, 2002], and "passive trust" credential protocols enable quick identity determination at low cost [Ghanea-Hercock, 2004]. However, these credential-based trust mechanisms require the presence of a trusted third party to verify the authenticity of credentials. Further, credential techniques may insist that agents reveal private information to verify identities [Yu and Winslett, 2003].

In contrast, "soft security" [Rasmusson and Jansson, 1996] implements trustworthiness assessment, based on social interactions among entities in a system, via behavior modeling of potential trustees. Soft security trust evaluation is useful either as a layer of protection secondary to hard security measures or as a stand-alone technique when hard security measures are not available or are deemed too restrictive. This research relies on two prominent methods for soft security trustworthiness evaluation: experience-based trust modeling (Section 2.3.2) and reputation-based trust modeling (Section 2.3.3).

2.3.2 EXPERIENCE-BASED TRUST MODELING

Experience-based trust modeling occurs when a truster uses the outcomes of its previous transactions with a trustee to estimate that trustee's future trustworthiness. Experience-based trust modeling is advantageous when agents have opportunities for numerous, repeated interactions. When the outcome of interactions are observable, transaction experiences provide a truster with trustworthiness feedback that is certain. Unfortunately, basing trust on transaction experiences means risk exposure is unavoidable; transactions based on little trust information must take place to evaluate a trustee's trustworthiness characteristics [Barber, et al., 2003]. Therefore, in systems with high likelihoods of trustee cheating, trusters should avoid experiences for initial trust model-building.

Numerous algorithms exist for maintaining trust models based on experiences with trustees. For example, Jonker and Treur propose both qualitative and quantitative trust metrics, which credit a trustee when a transaction produces a positive outcome, and discredit the trustee when a negative outcome is produced [Jonker and Treur, 1999]. Barber and Kim build experience-based trust models of information sources by computing a "dissimilarity measure" to determine the amount of incorrect information from a source [Barber and Kim, 2003]. Schillo, et al. use trust as an estimate of an agent's honesty, which is measured as the ratio of positive interactions to total interactions, to measure system performance in terms of isolation of deceptive agents [Schillo, et al., 2000] in the Iterated Prisoner's Dilemma game [Axelrod, 1984]. For Biswas et al., success is measured by the ability of the system to prevent manipulation of probabilistic reciprocity strategy by deceptive agents [Biswas, et al., 1999].

When no other trust information is available, experience-based models must assume some initial default trust assessment which, when inaccurate, can result in unfair losses to the truster (when initial trust assessment is too optimistic) or unfair losses to the trustee (when initial trust assessment is too pessimistic) [Dellarocas, 2000]. The truster can minimize risk exposure by conducting low-value transactions until an accurate experience-based model has been built. Risk exposure in information transactions can be circumvented by subjecting trustees to a preliminary test period, during which the use of knowledge acquired through direct interaction is deferred, until the base reputation is stabilized. However, the truster still loses any payments made to obtain information during the test period. Experience-based trust modeling also requires time and computational overhead over numerous, repeated transactions. This research introduces Adaptive Trust Modeling, which dynamically supplements experience-based trust models by incorporating reputation-based trust modeling when appropriate.

2.3.3 REPUTATION-BASED TRUST MODELING

Resnick observes that "…the assumption that what we know is a direct reflection of what we have perceived in the physical world has largely disappeared….People also build their knowledge structures on the basis of what they are told by others, orally, in writing, in pictures, and in gestures," [Resnick, 1991]. Not only can an agent obtain information by experiences, but, just as humans do, the agent can also utilize the experiences of others as a source of trust information. In reputation-based trust modeling, the truster learns trust information about the trustee by asking other agents in the system about their interactions with the trustee [Sen and Sajja, 2002; Shi, et al., 2005]. Reputation exchange is useful for quickly learning trustworthiness characteristics of potential trustees [Yu and Singh, 2002]. In systems with large populations and too few interaction opportunities, when experience-based trust modeling is infeasible, reputation exchange is advantageous. Reputation-based modeling reduces a truster's risk exposure; a truster risks only the price (if any) of reputations it purchases to build its reputation-based model, rather than the value of resources exchanged in an interaction to build its experience-based model. Agents entering a multi-agent system quickly can build trust models by requesting reputations from more knowledgeable agents. Reputation-based modeling serves as a catalyst in environments in which trusters would otherwise never risk transacting, as in online (e.g. eBay) purchases between buyers and sellers who are separated by geographic distance [Resnick, et al., 2000].

Reputation-based trust modeling allows the truster to form a trust model of the trustee without being exposed to the risk of uninformed experiences. However, the truster is still at risk when it decides to act on or believe the information it receives from others. In addition, the system must contain a base of trusted reputation providers if the truster is to form a stable model. Though a truster may assume its observations of transaction outcomes (the information used to build experience-based trust models) are certain, reputations (the information used to build reputation-based trust models) received from other agents introduce uncertainty, since reputation providers may be inaccurate or lying. Therefore, a truster has the additional task of assessing the accuracy of reputations it receives and the trustworthiness of the agents providing them. Barber and Kim assess the trustworthiness of recommenders in the same way that they assess the trustworthiness of trustees [Barber and Kim, 2002]. Jurca and Faltings attempt to improve the trustworthiness of the recommender base by providing incentives for recommenders to tell the truth [Jurca and Faltings, 2002; Jurca and Faltings, 2006], while Fan, et al., improve existing online reputation mechanisms by increasing the influence of more recent reputations [Fan, et al., 2005]. Reputation-based trust modeling still has difficulty in building initial trust models when the truster is new to the system (and therefore does not know which reputation providers can be trusted) or when the trustee is new to the system (and no reputation providers have formed opinions yet). In other words, some interaction must take place for reputation-based trust models to be built. Nevertheless, this form of agent "gossip" is valuable because it provides a cheap, low-risk form of communicating knowledge.

Several researchers have developed concepts to address the problem of initial trust assignments during the period before experiences or reputation information can be obtained. Bacharach explains that a truster can believe characteristics displayed by a trustee to the degree that those characteristics are difficult to duplicate by an impostor [Bacharach, 2002]. Based on this theory, an agent can trust another if it believes the descriptive meta-information the trustee agent displays is authentic. Determining how meta-information is structured and communicated, as well as how an agent models difficulty of impersonation, must be addressed. Halberstadt and Mui suggest classification by group membership and reputation assignment based on associated group reputations, but the implications of group prejudice on an individual agent must be examined [Halberstadt and Mui, 2001]. Dellarocas argues that a truster's risk from arbitrary assignment is minimized if trustees are motivated by punishment to tell the truth [Dellarocas, 2002]. This research addresses the problem of uncertainty in reputation-based trust models. While existing research assumes reputation providers are truthful [Klos and LaPoutre, 2004; Jurca and Faltings, 2006], this research proposes techniques for identifying the best reputation providers, even when provided reputations may be inaccurate.

2.4 Beyond the State of the Art: Adaptive Trust Modeling

This research presents several advances to the current state of the art. These contributions are outlined according to the research questions presented in Section 1.2.

2.4.1 RQ 1: ADAPTIVE TRUST MODELING

Research Question 1 asks: *How do characteristics of a truster's environment affect the usefulness of the truster's experience- and reputation-based models?* The contributions of Research Question 1 are 1) an Adaptive Trust Modeling technique for weighting experience- vs. reputation-based models to produce the most accurate and cost-effective aggregated model possible, and 2) a quantitative analysis of the tradeoffs between experience- and reputation-based models to determine the conditions under which each type of model is favorable.

Researchers have developed successful algorithms for either experience- [Jonker and Treur, 1999; Schillo, et al., 2000] or reputation-based [Shi, et al., 2005; Teacy, et al., 2005] trust modeling, assuming system conditions are conducive to either only experience-based (numerous repeated transactions) or only reputation-based (one-time transactions) approaches. However, each modeling type has strengths and weaknesses. Several environments can be considered "hybrids," in which both experience- and reputation-based trust modeling techniques are useful tools depending on changing system conditions. For example, online social networks make use of both experiences and reputations when participants seek out new friends via reputations, then decide whether to keep friends based on interactions over time. Ramchurn, et al., acknowledge that a truster's perspective on a trustee should be based on both reputations and the truster's "confidence" in the trustee (based on past interactions), but methods for determining the relative weights of reputation and confidence are not discussed [Ramchurn, et al., 2004]. Huynh, et al., combine trust information from four types of models ("interaction trust," "role-based trust," "witness reputation," and "certified reputation") but require "end users" to manually set the relative weights of each model type according to perceived system conditions [Huynh, et al., 2004].

Barber and Kim compare experience- vs. reputation-based trust modeling, confirming the intuitive notions that experience is effective over long term interaction histories, but reputations give an accurate picture more quickly, assuming reputation providers are accurate [Barber and Kim, 2003]. Adaptive Trust Modeling improves upon Barber and Kim's work by considering the accuracy of provided reputations and trustworthiness characteristics of trustees, important factors influencing the effectiveness of both experience- and reputation-based trust modeling. Further, Barber and Kim produce only a static combination of experience- and reputation-based modeling which does not change despite dynamic system conditions. Adaptive Trust Modeling takes advantage of both experience- and reputation-based trust modeling, dynamically conforming to a truster's needs as its system's conditions vary.

Several researchers have shown that considering reputations from other agents (called reputation providers) improves a truster's decision-making, but reputations are assumed to be known and accurate [Crandall and Goodrich, 2004; Klos and LaPoutre, 2004]. Similarly, Jurca and Faltings assume a trusted, centralized mechanism, dictating protocols for reputation communication, can be established to enforce truthful reputation telling [Jurca and Faltings, 2002; Jurca and Faltings, 2006]. Adaptive Trust Modeling addresses the real problem of obtaining accurate reputation information when reputation providers are inaccurate, either because of incompetence or malicious intent. By performing Error-Based Translation on reputation information, this research demonstrates how inaccurate, yet consistent reputations are utilized to increase the accuracy of a truster's reputation-based trust model.

Research examining trust over referral networks has made advances toward identifying reliable providers of reputation information [Huynh, et al., 2005; Yolum and Singh, 2003]. Further, work by Fullam and Barber explores merging several sources of information by simple averaging of a best subset of sources [Fullam and Barber, 2007]. However, Adaptive Trust Modeling is unique in that it not only identifies best reputation providers, but combines their reputations using a weighted averaging technique which takes into account the relative strengths of each provider.

2.4.2 RQ 2: ADAPTIVE COST SELECTION

Research Question 2 asks: *How should a truster assess the value of trust information (specifically, reputations), in light of the cost of that information, to determine what trust information to acquire?* The contribution of Research Question 2 is the Adaptive Cost Selection algorithm for assessing the value of trust information, enabling a truster to determine what information to acquire when cost is a factor.

Other research acknowledges the monetary value of trust information. Avery, et al., acknowledge the cost to produce evaluations (reputations), designing a mechanism in which side payments encourage buyers to collectively order consumption (experiences) to maximize efficient allocation of evaluations among themselves [Avery, et al., 1999]. Ramchurn, et al., state that when only a low level of trust exists between truster and trustee, the truster's effort to secure "guarantees" of trustworthy behavior is significantly increased [Ramchurn, et al., 2004]. Ghanea-Hercock examines the truster's problem of determining how much effort to devote to determining the trustworthiness of a potential trustee; while the work attempts to minimize a truster's effort ("cost"), the "passive trust" solution requires trustees to be identified by unchanging ID tags [Ghanea-Hercock, 2004]. Jurca and Faltings' incentive compatible reputation mechanism issues side payments for truthful reputations, recognizing that trusters value reputation information inherently and are willing to pay for it [Jurca and Faltings, 2006]. Huynh, et al., introduce "Certified Reputation," by which trustees actively deliver to trusters certified reputations third-party agents have produced (reputation providers have an incentive to provide truthful reputations) [Huynh, et al., 2006]. The Certified Reputation scheme, as does Jurca and Faltings' incentive compatible mechanism for reputation reporting, assumes reputation providers know an exact reputation to report and is unable to handle reputation provider error.

The Adaptive Cost Selection algorithm described in this research is unique in that it assesses the value of individual pieces of trust information (in particular, reputations), with the understanding that trust information may have varying degrees of accuracy. Adaptive Cost Selection minimizes the truster's costs when acquiring trust information by determining exactly how much and which trust information to acquire. Further, the algorithm identifies the optimal tradeoff between aggregate trust model accuracy and cost of acquired trust information to maximize the truster's payoff from transactions with trustees.

Chapter 3

ADAPTIVE TRUST MODELING: MERGING EXPERIENCE- AND REPUTATION-BASED TRUST MODELS

This chapter answers Research Question 1: *How do characteristics of a truster's environment affect the usefulness of the truster's experience- and reputation-based models?* Two objectives are accomplished: 1) introducing the Adaptive Trust Modeling tool for producing accurate aggregated trust models by weighting experiences and reputations, and 2) quantitatively analyzing the conditions under which each type of model is favorable. Section 3.1 explains Adaptive Trust Modeling, a tool for combining experience- and reputation-based models to produce the most accurate aggregate trust model possible. Adaptive Trust Modeling enables a truster to dynamically and automatically adapt its reliance on experience- or reputation-based trust as system conditions change. Section 3.2 examines how characteristics of a truster's environment (including availability of transaction observation opportunities and trustee trustworthiness dynamics) affect the usefulness of the truster's experience-based trust model. Section 3.3 examines how characteristics of a truster's environment (including accuracy and cost of available reputations) affect the usefulness of the truster's reputation-based trust model. This analysis of the tradeoffs between experience- and reputation-based models enables trusters to acquire the types of trust information they can utilize best.

3.1 Adaptive Trust Modeling

This section lays the groundwork for examining the roles experience- vs. reputation-based modeling play given a wide range of system conditions, with varying availability of transaction opportunities, trustee trustworthiness dynamics, reputation accuracy, and reputation cost. Protocols for transactions (Section 3.1.1) and reputation exchange (Section 3.1.2) are outlined, demonstrating the motivation for trust models. In Section 3.1.3, both experience- and reputation-based trust modeling are defined, with differences between the two types of models delineated. Section 3.1.4 presents Adaptive Trust Modeling, a technique for comparing experience- and reputation-based trust models by assigning weights based on expected model error. Adaptive Trust Modeling provides the basis for Section 3.2 and Section 3.3, which analyze relative trust model usefulness given varying system conditions, influenced by availability of transaction observation opportunities, trustee trustworthiness dynamics, reputation accuracy, and reputation cost. Adaptive Trust Modeling is important because it identifies the system parameters conducive to experience vs. reputation-based modeling, weighing the tradeoffs of each model to build a more accurate aggregate model.

3.1.1 TRANSACTIONS

This section defines the terminology and notation used in the explanation of Adaptive Trust Modeling. Further, transaction protocol assumptions are outlined. An understanding of transaction details is essential for recognizing the need for trust—and Adaptive Trust Modeling—in transactions.

This research defines a transaction as an (implicit or explicit) agreement between two agents to exchange resources, such as goods, services, or information, as shown in Figure 3-1. In this research, a transaction is modeled as a sequential protocol for the purpose of separating truster and trustee roles (though in some cases, truster and trustee make decisions simultaneously). In a sequential transaction protocol, the truster first makes its decision regarding whether to trust, attempting to predict the trustee's decision. The truster signals its decision to trust by delivering its *payment* to the trustee in expectation of the promised *resource*. After the truster has committed to the transaction, the trustee then makes its decision (regarding whether to fulfill the agreement). The trustee knows with certainty the outcome of the transaction, based on the extent to which it delivers the agreed upon resource.

The values of promised resources and payments are denoted as $P_{i,j}$, where i represents the agent delivering the payment (truster) or resource (trustee), and j represents the agent valuating the payment or resource. For the explanation given throughout this approach, agents i and j are denoted as either r (the agent acting as truster) or e (the agent acting as trustee). Therefore, $P_{r,r}$ represents the truster's valuation of the agreed upon price it will pay to purchase a resource in a transaction. Similarly, $P_{r,e}$ represents the trustee's valuation of that same agreed upon price to be paid by the truster to purchase the resource in a transaction. $P_{e,e}$ denotes the trustee's valuation of the resource it agrees to provide in a transaction, while $P_{e,r}$ denotes the truster's valuation of that same resource it agrees to receive in a transaction.

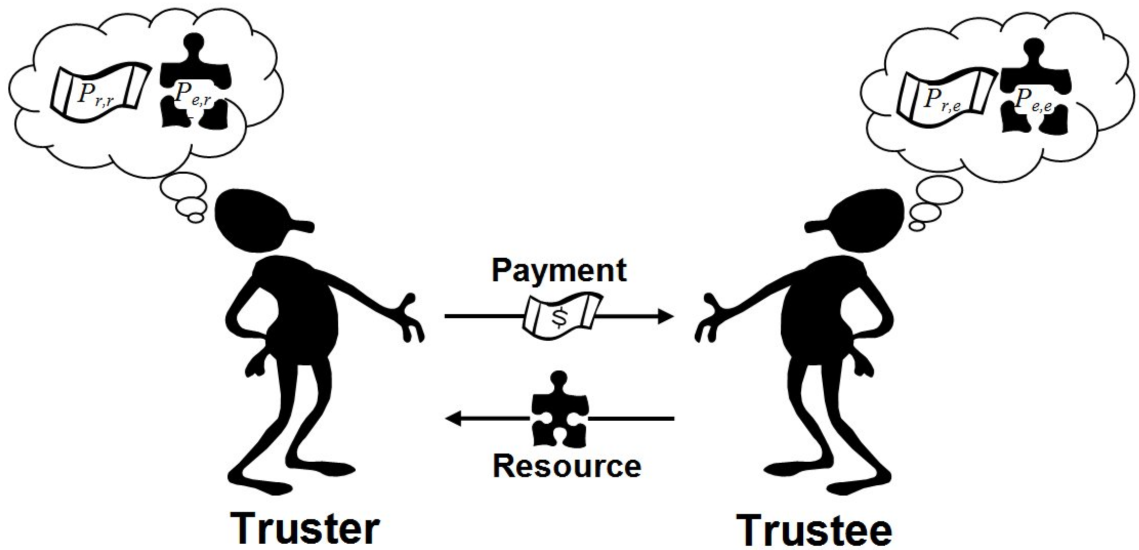


Figure 3-1. A sequential transaction between two agents. The truster first commits to trusting, sending payment (valued at $P_{r,r}$ and $P_{r,e}$ by truster and trustee, respectively). Then the trustee decides the extent of its own trustworthiness, in terms of the resource to deliver (valued at $P_{e,r}$ and $P_{e,e}$ by truster and trustee, respectively).

Note that the trustee and truster private valuations for a given payment or resource are different; it is assumed that an agent's valuation of the payment or resource it agrees to receive is greater than the agent's valuation of the payment or resource it agrees to provide (otherwise, the agent would have no incentive to participate in a transaction). Therefore:

$$P_{e,r} - P_{r,r} > 0, \text{ and}$$
$$P_{r,e} - P_{e,e} > 0.$$

Note that the values $P_{e,r}$, $P_{r,r}$, $P_{r,e}$, and $P_{e,e}$ in these equations represent valuations of *agreed upon* payments and resources; however, delivery of payments or resources at the represented value is not guaranteed if the trustee chooses not to fulfill its commitment and delivers less that the promised resource. Unless stated otherwise, this research assumes agreed upon resources and payments are constant over all transactions among all truster-trustee pairs.

A payoff matrix for a transaction is given in Figure 3-2. If the truster decides not to trust, both the truster and trustee receive a net payoff (denoted as P_r and P_e, respectively) of zero, since no transaction takes place. If the truster chooses to trust, it pays $P_{r,r}$ to the trustee, who perceives the payment's value as $P_{r,e}$. If the trustee chooses to fulfill its promise, it provides a resource it valuates as $P_{e,e}$ (valuated by the truster as $P_{e,r}$). In a binary (cheat vs. not cheat) case, if the trustee chooses to cheat, no resource is provided. When the trustee has multiple options for the value of resource it provides, the trustee may fail to fulfill the transaction agreement by providing a resource with an intermediate value (valuated by the truster as between zero and $P_{e,r}$) that falls short of the promised resource value. In fact, the truster's valuation of its net payoff (P_r), within the continuous range of $-P_{r,r}$ and $P_{e,r} - P_{r,r}$ inclusive, provides the basis for communicated reputation values, as discussed later in Section 3.1.2.

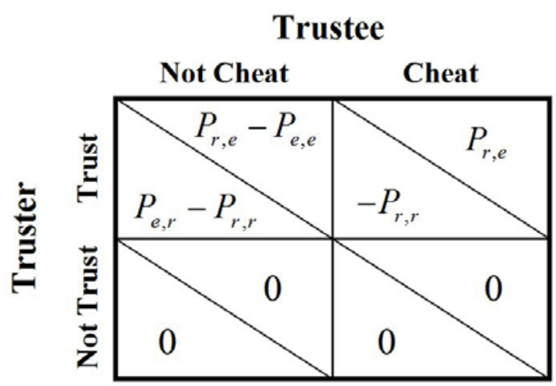


Figure 3-2. The payoff matrix for a transaction between truster and trustee, assuming a sequential protocol, in which the trustee's decision follows the truster's observable decision. In this figure, decisions are binary for both truster (trust vs. not trust) and trustee (cheat vs. not cheat), though this research permits a trustee to choose any level of trustworthiness such that the truster's valuation of its net payoff, P_{act}, is between $-P_{r,r}$ and $P_{e,r} - P_{r,r}$.

If the truster chooses to trust and the trustee chooses to fulfill its promise, then the net immediate payoffs to the truster (P_r) and trustee (P_e) are represented as:

$$P_r = P_{e,r} - P_{r,r}, \text{ and}$$

$$P_e = P_{r,e} - P_{e,e}.$$

If the truster chooses to trust and the trustee chooses to cheat (by delivering no payment), then the net immediate payoffs to the truster and trustee are represented as:

$$P_r = -P_{r,r}, \text{ and}$$

$$P_e = P_{r,e}.$$

The payoff matrix in Figure 3-2 shows that in a one-time transaction, the trustee's decision to cheat yields the highest possible payoff for the trustee. Therefore, in a one-time transaction, the truster should always choose not to trust, in order to avoid a loss. However, the ability of the truster to model the trustworthiness of the trustee over repeated transactions means a trustee must consider not only its immediate payoff. Instead, the trustee must also consider the impact of its decision on the future decisions of the truster, with the goal of ensuring the truster agrees to trust in future transactions. Further, as explained in Section 3.1.2, when trusters may exchange reputations about a trustee, a trustee must consider the impact of its transaction decision with one truster on future transaction opportunities with other trusters.

For the purposes of this research, transaction purchase costs (that is, $P_{r,r}$), as well as truster valuations of promised resources ($P_{e,r}$), are assumed to be the same for all transactions, constant over all transactions, and known by all agents, whether truster or trustee. Because this research deals with trust models and transaction decisions from the truster's perspective, this research discussion is concerned with transaction terms related to the truster's valuation: 1) its valuation of its own payment to the trustee ($P_{r,r}$), 2) its valuation of the trustee's agreed upon resource provision ($P_{e,r}$), and 3) its valuation of the trustee's actual resource provided ($P_{e,r,act}$). To simplify, this research will discuss a trustee's level of trustworthiness in terms of the truster's actual net payoff from a transaction, P_{act}, as compared to the truster's agreed upon net payoff (P_r) where

$$P_{act} = P_{e,r,act} - P_{r,r}. \qquad \text{Eqn 1}$$

Adaptive Trust Modeling maximizes the truster's net payoff (P_{act}) by predicting the trustee's actual resource provided ($P_{e,r,act}$). The terminology and transaction protocol assumptions outlined in this section provide the basis for the discussion of Adaptive Trust Modeling in Section 3.1.4.

3.1.2 REPUTATION EXCHANGE

This section delineates terminology and notation for reputation exchange within multi-agent systems. In many systems, trusters have the opportunity to exchange reputations, or information about the trustworthiness of a potential trustee. In this work, reputations about a trustee represent estimates of a truster's expected net payoff (P_{act}) received from the trustee (as compared to the truster's agreed upon net payoff P_r). In terms parallel to the discussion of transactions in Section 3.1.1, $P^r_{r,r}$ denotes the agreed upon payment (possibly zero) the truster pays to purchase the reputation, while $P^r_{r,e}$ represents the reputation provider's valuation of that same agreed upon payment (Figure 3-3). $P^r_{e,e}$ represents the reputation provider's valuation of the resource it loses by agreeing to participate in a reputation transaction. However, since the reputation provider is providing an information resource—the reputation—it does not "lose" that resource upon successful conduction of the transaction. Therefore, $P^r_{e,e}$ is assumed to be zero (this research does not address any indirect, intangible losses suffered by the reputation provider, such as losses due to increased competition from those to whom it provides reputations). $P^r_{e,r}$ represents the truster's valuation of the reputation it receives. Because the reputation is a form of information, the truster does not receive a tangible payoff from receipt of the information, so in immediate terms, $P^r_{e,r}$ is equal to zero. However, the truster may receive a future benefit from the reputation in the form of better trust decision-making in transactions, depending on the accuracy of the reputation provided (this benefit, termed *MarginalReward*, is explained in Chapter 4).

In summary, the net immediate payoffs to the truster and reputation provider, respectively, are represented as:

$$P^r_r = -P^r_{r,r}\text{, and}$$

$$P^r_e = P^r_{r,e}\,.$$

Because this research deals with trust models and transaction decisions from the truster's perspective, this research discussion is concerned with transaction terms related to the truster's valuation: 1) reputation cost, the truster's valuation of its own payment to the reputation provider ($P^r_{r,r}$), and 2) the truster's valuation of the future benefit, in terms of better trust decisions, received from the reputation (*MarginalReward*). It is possible for reputation costs to be zero, a special case. Throughout the remainder of this research, the cost of a reputation R_i, described generically as $P^r_{r,r}$, is denoted specifically as $Cost(R_i)$.

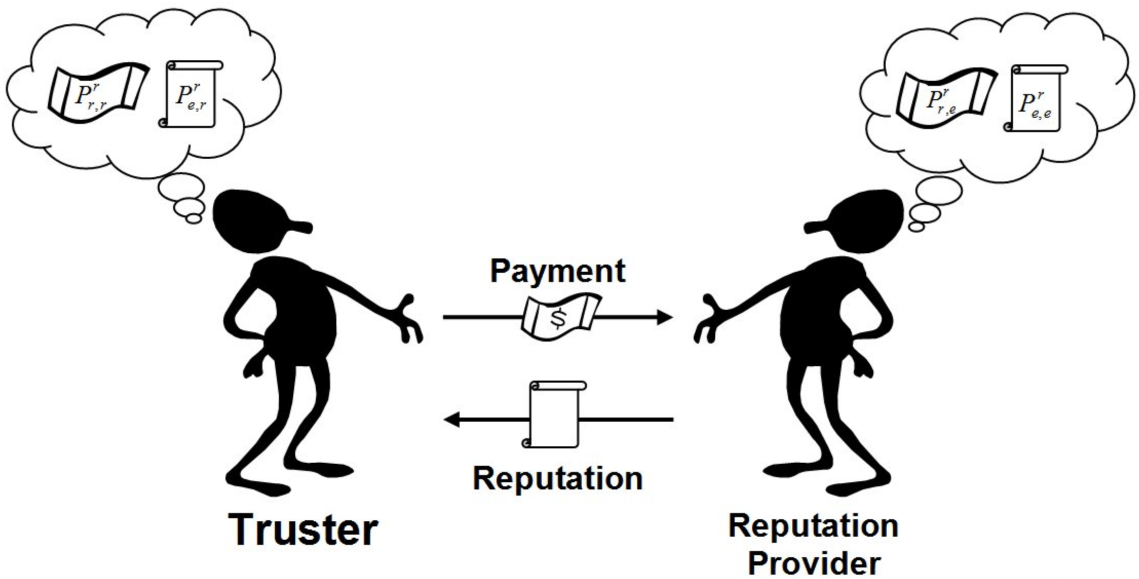


Figure 3-3. A sequential reputation transaction between a truster and a reputation provider. The truster first commits to purchasing the reputation, sending payment (valued at $P^r_{r,r}$ and $P^r_{r,e}$ by truster and reputation provider, respectively). Then the reputation provider decides the reputation to deliver.

The accuracy of a provided reputation is dependent upon both the quality of the reputation provider's aggregated trust model about the subject-agent (the transaction trustee) and the level of truthfulness with which the reputation provider chooses to communicate that model (Barber, et al., term these factors "competence" and "intent", respectively [Barber, et al., 2003]). In other words, a reputation provider with an inaccurate aggregated trust model may deliver a truthful, yet still inaccurate, reputation; conversely, a reputation provider with an accurate aggregated trust model may choose to communicate false, inaccurate reputations. Note that to build accurate reputation models and propagate accurate reputations throughout a multi-agent system, reputation-based modeling alone is not sufficient. At least some agents in the system must first conduct transactions (build experience-based models) with the subject-agent (barring the availability of other trust-building methods).

Adaptive Trust Modeling evaluates the accuracy of the reputations a truster receives, in comparison with the accuracy of the truster's experience-based trust model, to produce an accurate estimate of the truster's expected net payoff (P_{act}). Further, Adaptive Cost Selection (Chapter 4) assesses the tradeoff between reputation accuracy and cost, helping a truster purchase reputations to maximize net payoffs from trustees, yet minimize total reputation costs.

3.1.3 TRANSACTION TRUST MODELS

Transaction trust models assist trusters in predicting the outcome of transactions, with the purpose of selecting the most trustworthy trustees with whom to transact. Several techniques exist for building trust models based on previous experiences, reputations provided by others, group association, or credentials, for example. This research examines trust models based on a combination of two prominent "soft security" trust modeling techniques: experience- and reputation-based modeling.

To aid in making trust-related decisions, a truster has access to one or more trust models (based on experience or reputations) which generate suggestions related to future transaction opportunities. This research defines a *suggestion*, P_{sug}, to be a trust model's prediction about the actual expected net payoff (P_{act}) from a specified future transaction. The representation of suggestions as estimates of P_{act} is chosen because the P_{act} estimate is the truster's decision-point for determining whether to trust in a proposed transaction; the truster will choose to trust only if it believes P_{act} will be greater than zero. In contexts other than this research, suggestions may be defined differently. For example, suggestions may measure the trustee's information error when transactions concern the purchase of information [Barber and Fullam, 2003]. Or, suggestions may represent Boolean predictions of transaction success (termed "referrals" by Yu and Singh [Yu and Singh, 2002]), or graded measures of service quality [Huynh, et al., 2004; Ramchurn, et al., 2004] that may be subjective [Vidal, 2003]. Recently, significant research develops reputation ontologies, enabling heterogeneous agents with varied trust models to exchange reputation-based suggestions [Casare and Sichman, 2005; Pinyol, et al., 2007; Vercouter, et al., 2007].

Experience-based trust modeling [Barber and Kim, 2003; Jonker and Treur, 1999] occurs when a truster uses the outcomes of its previous transactions with a trustee to estimate that trustee's future trustworthiness. The observed outcomes of those previous transactions are completely certain. In some cases (as seen in human face-to-face transactions involving witnesses), the truster may observe a transaction between a third-party truster and the trustee; this observation may be included in its experience-based trust model if the certainty of the observation can be assured. Experience-based models are limited in accuracy, however, based on the availability of transaction observation opportunities regarding the potential trustee in question. If the number of observations making up a truster's experience-based trust model is few or none, that experience-based model will have relatively high error (Section 3.2.3 explains that the error of an experience-based model is dependent on the relationship between the number of transaction observations and the rate at which the trustee's behavior pattern changes).

This research assumes a simple experience-based trust model (similar to that employed by [Huynh, et al., 2004]), built by averaging payoffs (P_{act}) in previous observed transactions with the trustee to derive an experience-based model suggestion (called $P_{E,sug}$):

$$P_{E,sug} = \frac{\sum_{i=1}^{m} \chi_{t(i)} P_{act,i}}{\sum_{i=1}^{m} \chi_{t(i)}} \qquad \text{Eqn 2}$$

where previous observations may be weighted with discounting for age, either discretely:

$$\chi_t = \begin{cases} 1 \text{ for } 0 \le t \le \tau \\ 0 \text{ for } \tau < t \end{cases}$$

or continuously:

$$\chi_t = \frac{\chi_0}{(t+1)^{\alpha}}. \qquad \text{Eqn 3}$$

The variable t represents the age of the suggestion, in terms of discrete timesteps. When $\tau = \infty$ (discrete discounting case) or $\alpha = 0$ (continuous discounting case), no discounting occurs. Note that Adaptive Trust Modeling (Section 3.1.4), which combines suggestions from experience- and reputation-based trust models based on the accuracy of each model, does not specifically require the computation of experience-based suggestions based on the experience-averaging calculation above.

Reputation-based trust modeling [Sen and Sajja, 2002; Shi, et al., 2005] occurs when a truster builds its trust model of a potential trustee by requesting reputation suggestions, or estimates of P_{act}, from third-party reputation providers. Reputation-based trust modeling leverages the additional experience of other trusters (for example, a few experiences from many different trusters or extensive experience from a few trusters) to quickly build a trust model. However, the truster can not be certain about the accuracy of reputations received from reputation providers; providers may choose to lie about the trustee, or simply may not have their own accurate model from which to produce reputations.

The accuracy of a truster's experience- and reputation-based models depends on environment factors, including availability of transaction observation opportunities, trustee trustworthiness dynamics, and accuracy and cost of available reputations. When a truster has access to both experiences and reputations, the truster is faced with the dilemma of determining which type of model, experience- or reputation-based, should provide the suggestions the truster follows. In fact, a combination of suggestions from both types of models may yield a more accurate aggregate suggestion than either single model. Adaptive Trust Modeling weighs suggestions from both experience- and reputation-based models to produce accurate aggregate suggestions despite changes in system conditions.

3.1.4 Comparing Trust Models: Adaptive Trust Modeling

This section explains Adaptive Trust Modeling, a technique for maximizing the accuracy of a truster's trust-related decisions by dynamically utilizing suggestions from multiple trust models according to the accuracy of each model. While the weighting mechanism behind Adaptive Trust Modeling is quite simple, Adaptive Trust Modeling is a powerful tool for fulfilling two objectives of this research:

1) assessing the effectiveness of both experience- and reputation-based trust modeling, in terms of assigned weights, under varying system conditions (availability of transaction observation opportunities, trustee trustworthiness dynamics, and accuracy and cost of available reputations), and

2) dynamically combining experience- and reputation-based suggestions, depending on changing system conditions, to yield aggregate trust models that maintain accuracy by exploiting each model's strengths.

The Adaptive Trust Modeling technique assumes the truster must decide how to use suggestions from each model without necessarily knowing the content of (the value P_{sug} conveyed by) the suggestion. When this constraint is released, techniques such as outlier detection [Fullam and Barber, 2004] can be applied to make best use of suggestions once suggestion values are observed. The Adaptive Trust Modeling technique facilitates the discussion in Section 3.2 and Section 3.3 of how environment factors—including availability of transaction observation opportunities (Section 3.2.1), trustee trustworthiness dynamics (Section 3.2.2 and Section 3.2.3), reputation accuracy (Section 3.3.1), and reputation cost (Section 3.3.2)—influence preference for experience- over reputation-based trust models, or vice versa.

The Adaptive Trust Modeling mechanism is diagrammed in Figure 3-4. To measure its confidence in a trust model, the truster builds an error probability distribution to estimate the accuracy of the model's suggestions about a future transaction. This error probability distribution is built by aggregating the error of numerous previous suggestions, accounting for changes in accuracy over time. Specifically, a suggestion's error, P_{err}, is defined as the difference between that suggestion's predicted truster net payoff (called P_{sug}) and the truster's actual net payoff (P_{act}):

$$P_{err} = P_{sug} - P_{act}. \qquad \text{Eqn 4}$$

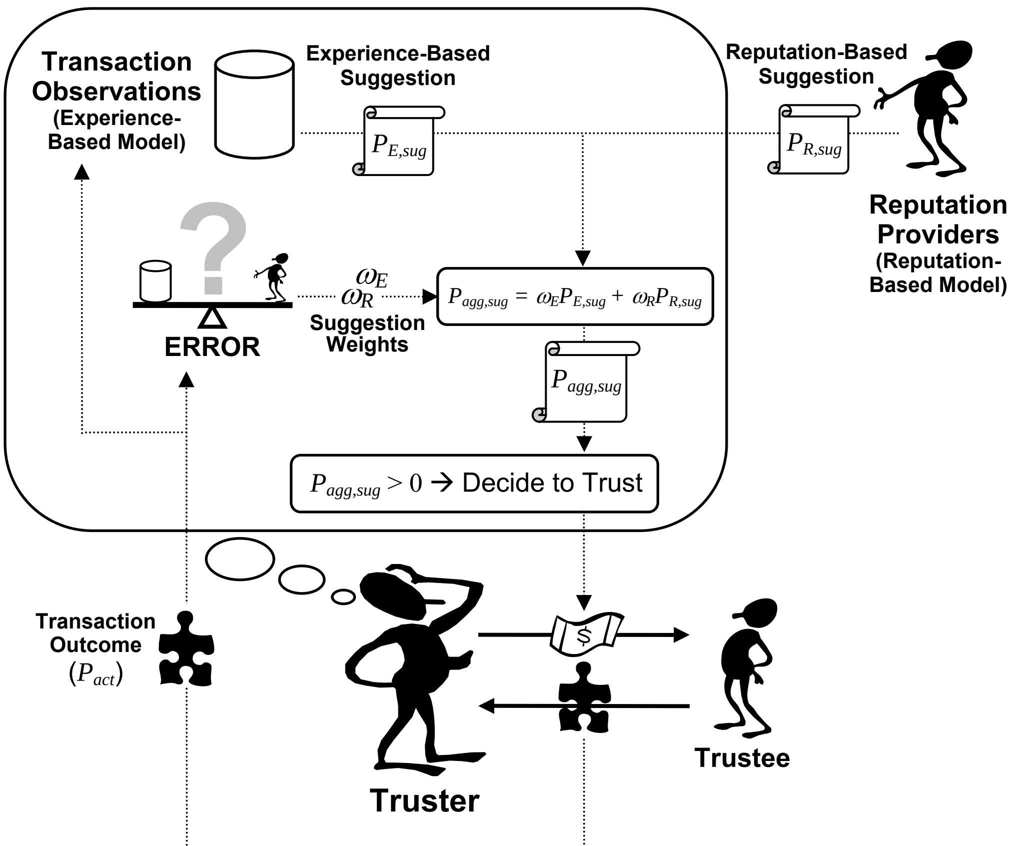


Figure 3-4. The Adaptive Trust Modeling technique. The truster decides whether to trust a potential trustee by performing a weighted average of suggestions from both experience- and reputation-based trust models. Weights are determined by relative error of each trust model. The transaction outcome is used to update both the truster's experience-based model (as an additional experience) and error estimates for each trust model.

As shown by Equation 4, two factors influence a trust model's error probability distribution: 1) the distribution of the model's suggestions P_{sug}, and 2) the trustee's actual behavior, as a distribution of the truster's actual net payoffs P_{act}. For ease of calculation and to demonstrate the relationships between model error, model suggestions, and trustee behavior, trustees are assumed to behave such that trustee behavior (truster net payoff) is normally distributed as $N(\mu_{beh}, \sigma_{beh})$; similarly, trust models are assumed to provide suggestions that are normally distributed as $N(\mu_{sug}, \sigma_{sug})$. Assumptions of normal distributions for trustee behavior ($N(\mu_{beh}, \sigma_{beh})$), trust model suggestions ($N(\mu_{sug}, \sigma_{sug})$), and, therefore, trust model error ($N(\mu_{err}, \sigma_{err})$) are reasonable because normal distributions appropriately describe many types of real-world behavior. For example, an eBay seller (trustee) may have slight deviations in her valuation accuracy of products she sells, or a referral broker (reputation provider) may deliver information with noise. The behavior of trustees who engage in occasional, strategic cheating can be approximated by normal distributions with some degree of success. Further, the normal distribution assumption simplifies mathematical derivations for trust model weights and aggregate model error, as discussed later in this section. As an extension to this research, this Adaptive Trust Modeling technique could be modified to accommodate patterns not easily accommodated by normal distributions (for example, lying reputation providers or strategically-cheating trustees whose behaviors follow multi-modal or Bernoulli distributions). These cases require more complicated computation (in some cases, by approximation), but the Adaptive Trust Modeling methodology remains unchanged.

Trust model suggestions (values of P_{sug}) are assumed to be uncorrelated to individual instances of trustee behavior (truster net payoffs P_{act}). That is, it is assumed that a trust model cannot predict individual instances of P_{act}, but can only estimate the general distribution $N(\mu_{sug}, \sigma_{sug})$. When suggestions are uncorrelated to individual trustee decisions, in the best case, a model will consistently suggest the mean of the trustee's behavior distribution, resulting in a suggestion distribution of $N(\mu_{beh}, 0)$ and error distribution of $N(0, \sigma_{beh})$. A model is even more accurate if each suggestion is correlated to the trustee's specific future decision, P_{act}, such that its suggestion distribution is $N(P_{act}, \sigma_{sug})$ for each given P_{act} and for some small or zero σ_{sug}, resulting in an error distribution of $N(0, \sigma_{sug})$. A spectrum of correlation may be implied if a trust model keeps pace with a trustee's changes in behavior distribution, depending on the relationship between the variation in the trustee's behavior (σ_{sug}) and the frequency with which the truster changes its behavior distribution. For example, a trustee who maintains a very low σ_{beh} value yet changes μ_{sug} very frequently may be dually described as following a single behavior distribution with constant μ_{sug} and high σ_{beh} value. This research assumes trust model suggestions are not correlated to individual trustee decisions. Further, the research assumes trustees do not change behavior distributions, except in Section 3.3.1.2, where it is assumed reputation-based trust models do keep pace with trustee behavior distribution changes.

The research assumes, unless otherwise stated, that $\mu_{sug} = \mu_{beh}$ for all trust models; that is, trust models have error only due to distribution standard deviation, not mean. Therefore,

$$\mu_{err} = \mu_{sug} - \mu_{beh} = 0.$$

Section 3.2.1 explains why this assumption is valid for experience-based trust models. Section 3.3.1.2 includes a discussion of scenarios in which $\mu_{sug} \neq \mu_{beh}$ for reputation-based models and provides an accommodation, called Error-Sensitive Translation. The accuracy and usefulness of trust models are measured by their error distributions. The mean (μ_{err}) of a model's error distribution is an indicator of the *accuracy* of future predictions suggested by the model; distributions with means near zero imply greater accuracy that those with means farther from zero (assuming the same standard deviation). The standard deviation (σ_{err}) of a model's error distribution indicates the *consistency*, or usefulness, of future predictions suggested by the model; models with high consistency (low standard deviation) are expected to yield predictions of high usefulness.

Assuming that trust model suggestions (P_{sug}) and trustee behavior (P_{act}) are uncorrelated, derived from independent distributions ($N(\mu_{sug}, \sigma_{sug})$ and $N(\mu_{beh}, \sigma_{beh})$, respectively), the following relationship holds:

$$\sigma_{err} = \sqrt{\sigma_{sug}^2 + \sigma_{beh}^2}\,. \qquad \text{Eqn 5}$$

That is, a trust model's error is the sum of error due to variations in its suggestions and error due to variations in the trustee's behavior.

Trust model error probability distributions, as built up by observing the results of previous transactions, determine how best to combine suggestions from multiple trust models to achieve an aggregated suggestion about a future transaction with the lowest expected error. When averaging *n* suggestions, each taken from normal distributions

$N(\mu_{i,sug}, \sigma_{i,sug})$, the resulting aggregate suggestion belongs to the distribution (assumed to be normal) $N(\mu_{agg,sug}, \sigma_{agg,sug})$, where

$$\mu_{agg,sug} = \frac{\sum_{i=1}^{n} \mu_{i,sug}}{n} \text{ and} \qquad \text{Eqn 6}$$

$$\sigma_{agg,sug} = \frac{\sqrt{\sum_{i=1}^{n}\left(\sigma_{i,sug}^2 + \left(\mu_{i,sug} - \mu_{agg,sug}\right)^2\right)}}{n}$$

[Fullam and Barber, 2007].

Since it is assumed currently that $\mu_{i,sug} = \mu_{beh}$ for all trust models, $\sigma_{agg,sug}$ reduces to:

$$\sigma_{agg,sug} = \frac{\sqrt{\sum_{i=1}^{n}\left(\sigma_{i,sug}^2\right)}}{n}.$$

A truster's goal is to minimize expected error of the aggregated suggestion $P_{agg,sug}$ (and thus, expected error standard deviation $\sigma_{agg,err}$), as aggregated from experience- and reputation-based suggestions ($P_{E,sug}$ and $P_{R,sug}$). The value of $\sigma_{agg,err}$ is minimized by minimizing $\sigma_{agg,sug}$, since, as an extension of Equation 5,

$$\sigma_{agg,err} = \sqrt{\sigma_{agg,sug}^2 + \sigma_{beh}^2} \qquad \text{Eqn 7}$$

When trust models' suggestion distributions have non-uniform standard deviation (in other words, some trust models are more accurate than others), $\sigma_{agg,sug}$ can be minimized by performing weighted linear regression, in which signals (suggestions) from variables (trust models) of non-uniform variance are weighted to favor those variables with least variance [Mandel, 1964]:

$$\sigma_{agg,sug} = \sqrt{\sum_{i=1}^{n}\left(\omega_i \sigma_{i,sug}\right)^2} \qquad \text{Eqn 8}$$

In Equation 8 above, ω_i represents the weight given to a specific suggestion $P_{i,sug}$ when performing a weighted average to arrive at an aggregated suggestion:

$$P_{agg,sug} = \sum_{i=1}^{n} \omega_i P_{i,sug} \qquad \text{Eqn 9}$$

where

$$\sum_{i=1}^{n} \omega_i = 1 . \qquad \text{Eqn 10}$$

The objectives of this research include understanding the differences between experience- and reputation-based trust modeling types, specifically, identifying the conditions under which one or the other is preferred. Therefore, the discussion in this section assumes a truster maintains two trust models: an experience-based trust model and a reputation-based model with error probability distributions denoted as $N(\mu_{E,err}, \sigma_{E,err})$ and $N(\mu_{R,err}, \sigma_{R,err})$, respectively. The suggestions from the truster's reputation-based model originate from a single reputation provider or represent aggregations from several reputation providers (aggregating suggestions from multiple reputation providers is discussed in Section 3.3.2).

Suggestions from experience- and reputation-based models are represented as $N(\mu_{E,sug}, \sigma_{E,sug})$ and $N(\mu_{R,sug}, \sigma_{R,sug})$ respectively. Therefore,

$$P_{agg,sug} = \omega_E P_{E,sug} + \omega_R P_{R,sug} \text{ and}$$

$$\sigma_{agg,sug} = \sqrt{\left(\omega_E \sigma_{E,sug}\right)^2 + \left(\omega_R \sigma_{R,sug}\right)^2} , \qquad \text{Eqn 11}$$

where ω_E and ω_R represent weights for the experience- and reputation-based model suggestions, respectively, and

$$\omega_E + \omega_R = 1 . \qquad \text{Eqn 12}$$

Substituting Equation 12 into Equation 11 (expressing ω_E in terms of ω_R):

$$\sigma_{agg,sug} = \sqrt{\left(1-\omega_R\right)^2 \sigma_{E,sug}^2 + \omega_R^2 \sigma_{R,sug}^2} .$$

Simplifying,

$$\sigma_{agg,sug} = \sqrt{\left(1-2\omega_R + \omega_R^2\right) \sigma_{E,sug}^2 + \omega_R^2 \sigma_{R,sug}^2}$$

$$\sigma_{agg,sug} = \sqrt{\sigma_{E,sug}^2 - 2\omega_R \sigma_{E,sug}^2 + \omega_R^2 \sigma_{E,sug}^2 + \omega_R^2 \sigma_{R,sug}^2}$$

$$\sigma_{agg,sug} = \sqrt{\left(\sigma_{E,sug}^2 + \sigma_{R,sug}^2\right) \omega_R^2 + \left(-2\sigma_{E,sug}^2\right) \omega_R + \sigma_{E,sug}^2} .$$

To find the optimal weight $\omega_{R,\sigma_{agg,err,min}}$ for minimizing $\sigma_{agg,sug}$ (and $\sigma_{agg,err}$), the derivative of $\sigma_{agg,sug}$ is set to zero to solve for $\omega_{R,\sigma_{agg,err,min}}$.

$$\frac{\delta}{\delta\omega_R}\left(\sigma_{agg,sug,min}\left(\omega_R\right)\right)=0$$

$$\frac{\delta}{\delta\omega_R}\left(\sqrt{\left(\sigma_{E,sug}^2+\sigma_{R,sug}^2\right)\omega_R^2-\left(2\sigma_{E,sug}^2\right)\omega_R+\sigma_{E,sug}^2}\right)=0$$

$$\frac{1}{2}\frac{2\left(\sigma_{E,sug}^2+\sigma_{R,sug}^2\right)\omega_{R,\sigma_{agg,err,min}}-2\sigma_{E,sug}^2}{\sqrt{\left(\sigma_{E,sug}^2+\sigma_{R,sug}^2\right)\omega_{R,\sigma_{agg,err,min}}^2-\left(2\sigma_{E,sug}^2\right)\omega_{R,\sigma_{agg,err,min}}+\sigma_{E,sug}^2}}=0$$

$$2\left(\sigma_{E,sug}^2+\sigma_{R,sug}^2\right)\omega_{R,\sigma_{agg,err,min}}-2\sigma_{E,sug}^2=0$$

$$\omega_{R,\sigma_{agg,err,min}}=\frac{\sigma_{E,sug}^2}{\sigma_{E,sug}^2+\sigma_{R,sug}^2}, \qquad \text{Eqn 13}$$

which is equivalent to

$$\omega_{R,\sigma_{agg,err,min}}=\frac{\frac{1}{\sigma_{R,sug}^2}}{\frac{1}{\sigma_{E,sug}^2}+\frac{1}{\sigma_{R,sug}^2}}.$$

Solving also for $\omega_{E,\sigma_{agg,err,min}}$:

$$\omega_{E,\sigma_{agg,err,min}}=\frac{\sigma_{R,sug}^2}{\sigma_{E,sug}^2+\sigma_{R,sug}^2}, \qquad \text{Eqn 14}$$

which is equivalent to:

$$\omega_{E,\sigma_{agg,err,min}}=\frac{\frac{1}{\sigma_{E,sug}^2}}{\frac{1}{\sigma_{E,sug}^2}+\frac{1}{\sigma_{R,sug}^2}}.$$

Or, more generally, for the case of suggestions from many different trust models,

$$\omega_{i,\sigma_{agg,err,min}} = \frac{\frac{1}{\sigma_{i,sug}^2}}{\sum_j \frac{1}{\sigma_{j,sug}^2}}. \qquad \text{Eqn 15}$$

Equation 15 is a well-known technique in weighted regression for assigning weights based on inverse variance of variables' signal distributions [Mandel, 1964]. Note that the trustee behavior distribution (σ_{beh}) being modeled does not influence weights assigned to suggestions from each trust model.

Substituting equations for $\omega_{E,\sigma_{agg,err,min}}$ and $\omega_{R,\sigma_{agg,err,min}}$ into Equation 11, $\sigma_{agg,sug,min}$ is computed:

$$\sigma_{agg,sug,min} = \sqrt{\left(\omega_{E,\sigma_{agg,err,min}} \sigma_{E,sug}\right)^2 + \left(\omega_{R,\sigma_{agg,err,min}} \sigma_{R,sug}\right)^2}$$

$$\sigma_{agg,sug,min} = \sqrt{\left(\left(\frac{\frac{1}{\sigma_{E,sug}^2}}{\frac{1}{\sigma_{E,sug}^2} + \frac{1}{\sigma_{R,sug}^2}}\right)\sigma_{E,sug}\right)^2 + \left(\left(\frac{\frac{1}{\sigma_{R,sug}^2}}{\frac{1}{\sigma_{E,sug}^2} + \frac{1}{\sigma_{R,sug}^2}}\right)\sigma_{R,sug}\right)^2}$$

$$\sigma_{agg,sug,min} = \sqrt{\frac{\frac{1}{\sigma_{E,sug}^2}}{\left(\frac{1}{\sigma_{E,sug}^2} + \frac{1}{\sigma_{R,sug}^2}\right)^2} + \frac{\frac{1}{\sigma_{R,sug}^2}}{\left(\frac{1}{\sigma_{E,sug}^2} + \frac{1}{\sigma_{R,sug}^2}\right)^2}}$$

$$\sigma_{agg,sug,min} = \sqrt{\frac{\frac{1}{\sigma_{E,sug}^2} + \frac{1}{\sigma_{R,sug}^2}}{\left(\frac{1}{\sigma_{E,sug}^2} + \frac{1}{\sigma_{R,sug}^2}\right)^2}}$$

$$\sigma_{agg,sug,min} = \sqrt{\frac{1}{\frac{1}{\sigma_{E,sug}^2} + \frac{1}{\sigma_{R,sug}^2}}}$$

$$\sigma_{agg,sug,min} = \sqrt{\frac{\sigma_{E,sug}^2 \sigma_{R,sug}^2}{\sigma_{E,sug}^2 + \sigma_{R,sug}^2}}$$

$$\sigma_{agg,sug,min} = \frac{\sigma_{E,sug}\sigma_{R,sug}}{\sqrt{\sigma_{E,sug}^2 + \sigma_{R,sug}^2}} \qquad \text{Eqn 16}$$

More generally, for the case of suggestions from many different trust models,

$$\sigma_{agg,sug,min} = \sqrt{\frac{1}{\sum_j \frac{1}{\sigma_{j,sug}^2}}} \text{ and} \qquad \text{Eqn 17}$$

$$\sigma_{agg,err,min} = \sqrt{\frac{1}{\sum_j \frac{1}{\sigma_{j,sug}^2}} + \sigma_{beh}^2} . \qquad \text{Eqn 18}$$

Considering only an experience-based and a reputation-based model,

$$\sigma_{agg,err,min} = \sqrt{\frac{\sigma_{E,sug}^2\sigma_{R,sug}^2}{\sigma_{E,sug}^2 + \sigma_{R,sug}^2} + \sigma_{beh}^2} . \qquad \text{Eqn 19}$$

Figure 3-5 charts aggregate suggestion standard deviation, $\sigma_{agg,sug}$, for varying combinations of ω_E and ω_R, emphasizing the location of $\sigma_{agg,sug,min}$.

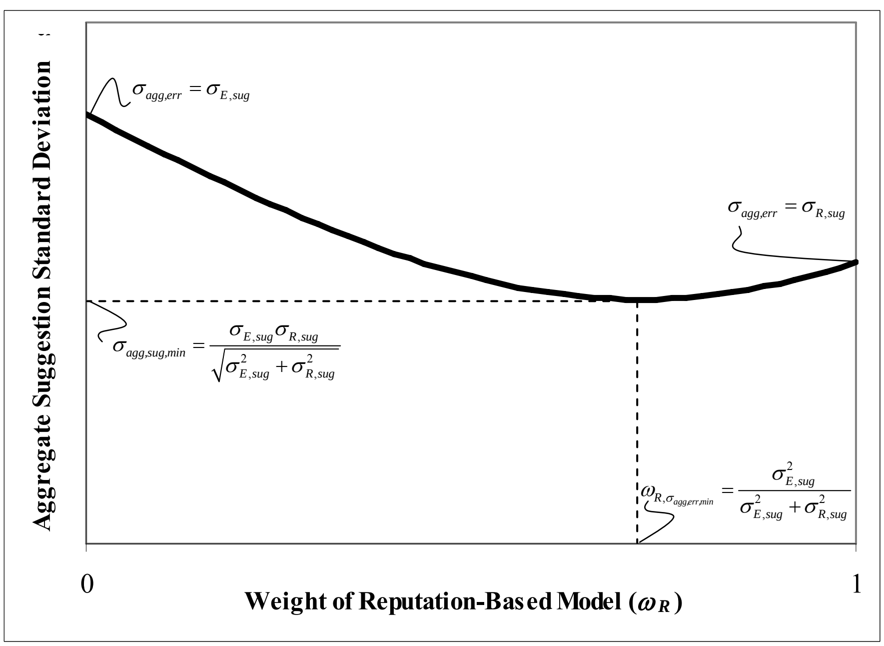


Figure 3-5. Aggregate suggestion standard deviation ($\sigma_{agg,sug}$) as a function of reputation-based model weight (ω_R). The value of $\sigma_{agg,sug}$ is minimized when weights are computed according to Equation 15.

According to Equation 5, the reader might note that a trust model's error is minimized when $\sigma_{sug} = 0$. It might seem as though a reputation provider, seeking to maximize its influence on the truster, could maximize the weight (according to Equation 13) of the reputation suggestions it provides, minimizing its error simply by making consistent suggestions (resulting in $\sigma_{sug} = 0$). If the assumption that $\mu_{sug} = \mu_{beh}$ holds (under which Equation 13 is derived), and $\sigma_{R,sug}$ does equal zero, then the reputation-based trust model supplied by the reputation provider does indeed provide the most accurate possible suggestions, and ω_R should be correspondingly high. If it is possible that $\mu_{sug} \neq \mu_{beh}$ (in other words, the reputation provider simply picks some default, consistent suggestion value), then additional techniques (such as Error-Sensitive Translation, as described in Section 3.3.1.2) may be employed to assess the accuracy of the reputation provider's suggestions. However, techniques such as Error-Sensitive Translation require the observation of multiple reputation suggestions before those suggestions are put to use. As a result, the reputation provider's ability to influence the truster's aggregate suggestion is delayed significantly; hence, the reputation provider achieves no real influence gain over the truster by simply reporting an arbitrary, consistent suggestion.

A question arises as to the validity of building estimates of suggestion probability distributions (approximating $\sigma_{R,sug}$) for reputation-based trust models. Because reputation-based models are particularly useful when transaction observation opportunities are scarce (and thus, experience-based models are weak), the truster has few data points about the trustee in question with which to build estimates of reputation-based suggestion probability distributions. However, the truster may base its reputation-based suggestion probability distribution—at least initially—on the model's suggestions about other trustees, as long as the truster believes the model maintains equivalent suggestion accuracy from trustee to trustee. This "transference of accuracy" assumption agrees with the intuitive notion of utilizing a reputation provider for advice about an unfamiliar potential trustee if the provider has delivered accurate suggestions about past transactions with other trustees.

Figure 3-6 compares $\sigma_{agg,err}$ given $\sigma_{E,sug}$ and $\sigma_{R,sug}$ (in this figure, σ_{beh} equals zero) for Adaptive Trust Modeling against 1) a "Select One" technique and 2) a "Simple Averaging" technique. Using the Select One technique, the single suggestion anticipated to be most accurate is employed as the aggregated suggestion:

$$P_{agg,sug} = \begin{cases} P_{E,sug} & \text{for } \sigma_{E,sug} \le \sigma_{R,sug} \\ P_{R,sug} & \text{for } \sigma_{E,sug} > \sigma_{R,sug} \end{cases}.$$

Therefore,

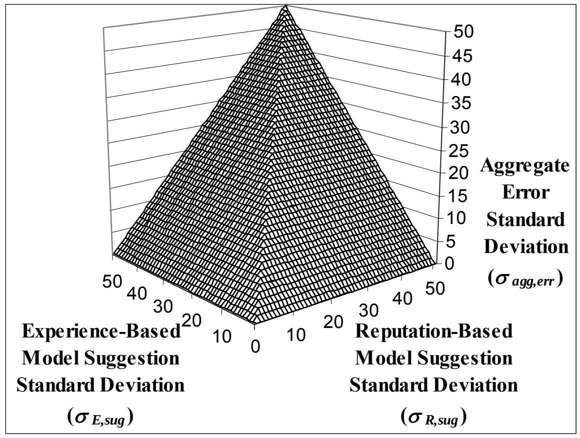
$$\sigma_{agg,err} = min\begin{cases} \sqrt{\sigma_{E,sug}^2 + \sigma_{beh}^2} \\ \sqrt{\sigma_{R,sug}^2 + \sigma_{beh}^2} \end{cases}.$$

Using the Simple Averaging technique, $\omega_E = \omega_R = 0.5$:

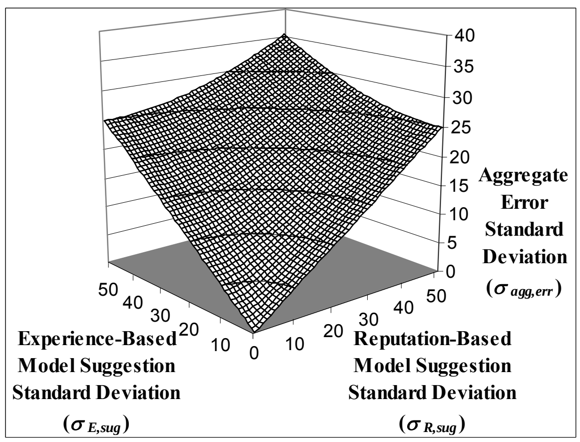
$$P_{agg,sug} = 0.5P_{E,sug} + 0.5P_{R,sug} \text{ and}$$

$$\sigma_{agg,err} = \sqrt{\left(0.5\sigma_{E,sug}\right)^2 + \left(0.5\sigma_{R,sug}\right)^2 + \sigma_{beh}^2}. \qquad \text{Eqn 20}$$

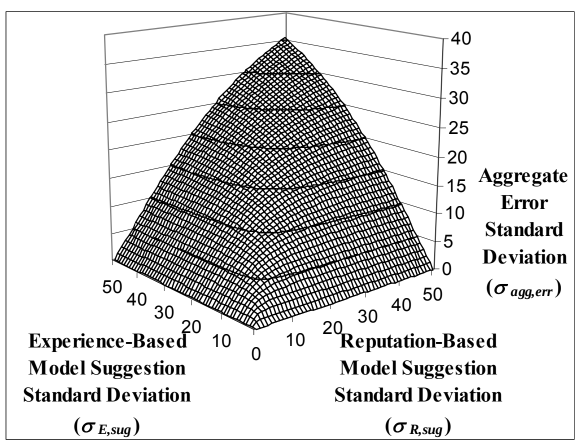
The Select One technique (Figure 3-6a) achieves a low $\sigma_{agg,err}$ when either $\sigma_{E,sug}$ or $\sigma_{R,sug}$ is significantly lower than the other (the occasions when weight combinations of zero and one yield lowest $\sigma_{agg,err}$ anyway). However, when $\sigma_{E,sug}$ and $\sigma_{R,sug}$ are similar in value, the Select One technique fails to benefit from the power of averaging, resulting in higher $\sigma_{agg,err}$ values than the Adaptive Trust Modeling and Simple Averaging cases. Simple Averaging (Figure 3-6b) achieves a low $\sigma_{agg,err}$ when $\sigma_{E,sug}$ and $\sigma_{R,sug}$ are similar in value (when 0.5-0.5 weight combinations yield lowest $\sigma_{agg,err}$ anyway). When $\sigma_{E,sug}$ and $\sigma_{R,sug}$ are very different, however, $\sigma_{agg,err}$ values due to the Simple Averaging technique are needlessly high because the inaccurate trust model, in addition to the accurate trust model, is included in the aggregate suggestion.



(a)



(b)



(c)

Figure 3-6. Using (a) the Select One technique, (b) Simple Averaging, and (c) Adaptive Trust Modeling to compute aggregate error standard deviation, $\sigma_{agg,err}$, given experience- and reputation-based model suggestion standard deviations ($\sigma_{E,sug}$ and $\sigma_{R,sug}$ respectively), when σ_{beh} equals 0.

Adaptive Trust Modeling (Figure 3-6c) maximizes the benefit of both the Select One and Simple Averaging techniques by dynamically identifying the best combination of weights for all pairs of $\sigma_{E,sug}$ and $\sigma_{R,sug}$. Figure 3-7 shows the optimal ω_R (yielding lowest $\sigma_{agg,err}$) for given pairs of $\sigma_{E,sug}$ and $\sigma_{R,sug}$. According to Equation 14 and shown in Figure 3-7, when $\sigma_{E,sug}$ equals zero, the experience-based model's suggestion is completely favored ($\omega_{E,\sigma_{agg,err,min}}$ = 1) and the reputation-based model's suggestion may be discarded ($\omega_{R,\sigma_{agg,err,min}}$ = 0). Similarly, when $\sigma_{R,sug}$ equals zero, the reputation-based model's suggestion is completely favored ($\omega_{R,\sigma_{agg,err,min}}$ = 1) and the experience-based model's suggestion may be discarded ($\omega_{E,\sigma_{agg,err,min}}$ = 0). When both $\sigma_{E,sug}$ and $\sigma_{R,sug}$ equal zero, any pair of weights may be selected (provided $\omega_E + \omega_R = 1$), yielding the same $\sigma_{agg,err,min}$. More generally, when $\sigma_{R,sug}$ is greater than $\sigma_{E,sug}$, $\omega_{R,\sigma_{agg,err,min}}$ is less than $\omega_{E,\sigma_{agg,err,min}}$, and vice versa.

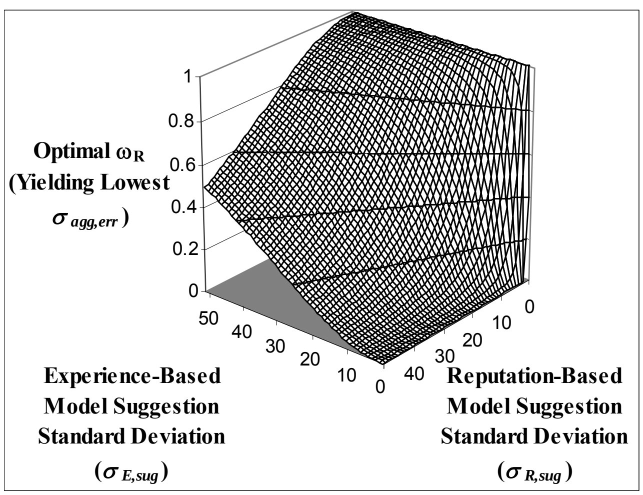
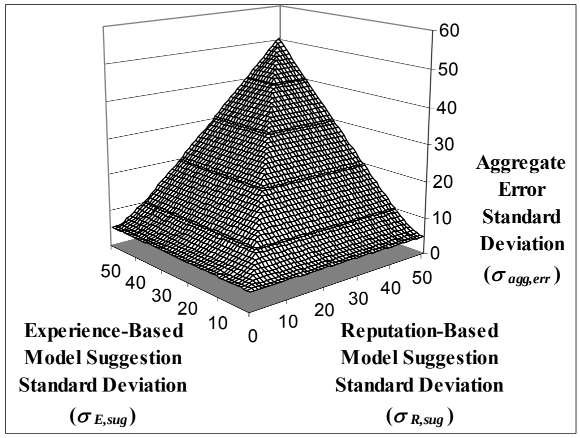


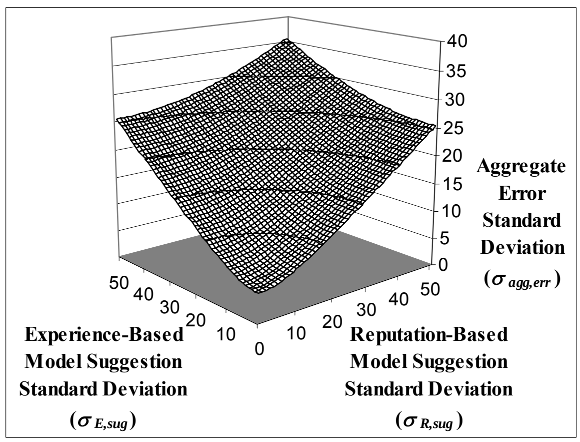
Figure 3-7. Optimal weights for a truster's reputation-based model (ω_R yielding lowest aggregate error standard deviation, $\sigma_{agg,err}$) given experience- and reputation-based model suggestion standard deviations ($\sigma_{E,sug}$ and $\sigma_{R,sug}$, respectively). When $\sigma_{E,sug}$ is zero (experience-based model is perfectly accurate), ω_R is zero (thus ω_E is one, and experience-based model is utilized exclusively). Conversely, when $\sigma_{R,sug}$ is zero (reputation-based model is perfectly accurate), ω_R is one reputation-based model is utilized exclusively).

Figure 3-8 and Figure 3-9 show $\sigma_{agg,err}$ for the Select One, Simple Averaging, and Adaptive Trust Modeling techniques when σ_{beh} equals 5 and 25, respectively. These figures demonstrate that incremental increases in $\sigma_{E,sug}$ and $\sigma_{R,sug}$ cause lower corresponding increases in $\sigma_{agg,err}$ when σ_{beh} is larger. The error caused by trustee behavior variation (σ_{beh}) overshadows the error caused by suggestion variation ($\sigma_{E,sug}$ and $\sigma_{R,sug}$).

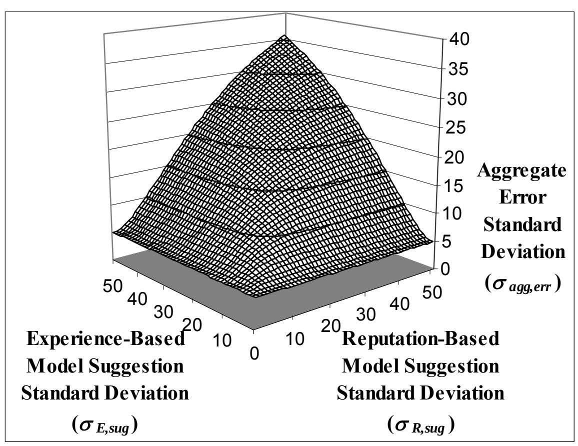
Adaptive Trust Modeling provides a more accurate alternative to Select One and Simple Averaging techniques; experience- and reputation-based models are combined according to the accuracy of each model (using weights given by Equation 15). Adaptive Trust Modeling improves upon research by Barber and Kim, Huynh, et al., and Ramchurn, et al., all of which combine multiple trust models but do not automatically relate weights to the relative accuracy of each model [Barber and Kim, 2003; Huynh, et al., 2004; Ramchurn, et al., 2004]. Adaptive Trust Modeling dynamically computes model weights based on model accuracy, which may vary across changing system conditions. The following sections demonstrate how Adaptive Trust Modeling maximizes the accuracy of the truster's aggregate trust model as the accuracy of experience-based models (Section 3.2) and reputation-based models (Section 3.3) change. Further, a quantitative analysis is performed of the tradeoffs between experience- and reputation-based models to determine the conditions under which each type of model is favorable.



(a)

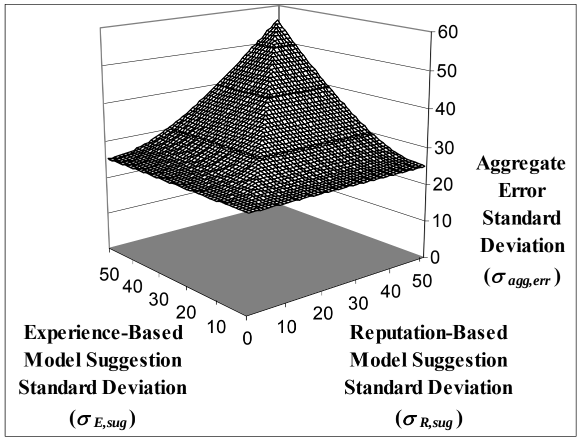


(b)

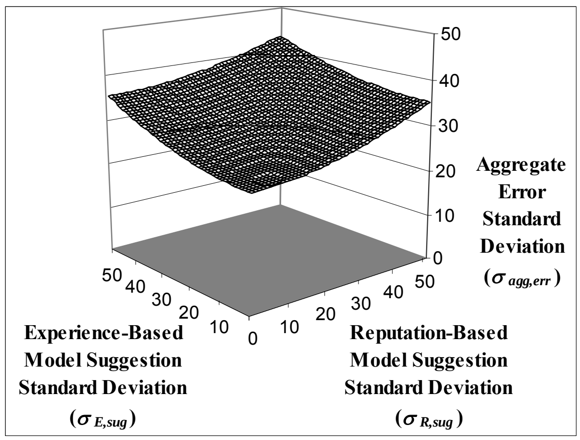


(c)

Figure 3-8. Using (a) the Select One technique, (b) Simple Averaging, and (c) Adaptive Trust Modeling to compute aggregate error standard deviation, $\sigma_{agg,err}$, given experience- and reputation-based model suggestion standard deviations ($\sigma_{E,sug}$ and $\sigma_{R,sug}$, respectively), when σ_{beh} equals 5.



(a)



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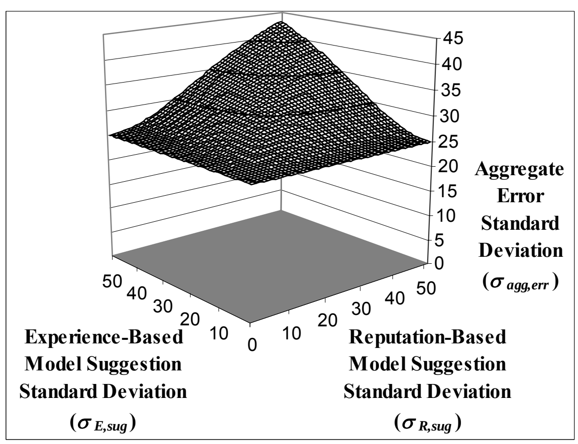


(c)

Figure 3-9. Using (a) the Select One technique, (b) Simple Averaging, and (c) Adaptive Trust Modeling to compute aggregate error standard deviation, $\sigma_{agg,err}$, given experience- and reputation-based model suggestion standard deviations ($\sigma_{E,sug}$ and $\sigma_{R,sug}$, respectively), when σ_{beh} equals 25.

3.2 Experience-Based Trust Model Usability Factors

This section discusses environment factors affecting the accuracy of experience-based trust models, including availability of transaction observation opportunities and trustee trustworthiness dynamics. When reputation-based models are mentioned for comparison purposes, a general, aggregated reputation-based model is assumed, since the details of selecting and combining reputations are not discussed until Section 3.3.2. Experiments in Section 3.2.1 show that experience-based models become more accurate as a truster's number of transaction observations increases; consequently, Adaptive Trust Modeling favors a truster's experience-based model as number of observations increases. Section 3.2.2 demonstrates that the building of a truster's experience-based model is slowed when the potential trustee is untrustworthy; as a result, the truster relies more on its reputation-based model. Finally, Section 3.2.3 shows that increased frequency of trustee behavior changes permits fewer transaction observations before an experience-based model is obsolete; therefore, reputation-based models prove more reliable when trustee trustworthiness is dynamic. In all cases, Adaptive Trust Modeling produces aggregated suggestions that are more accurate than Simple Averaging and either single (experience- or reputation-based) model alone.

3.2.1 Availability of Transaction Observation Opportunities

Experience-based models become more accurate as more transaction outcomes are observed. Because a truster is completely certain of each transaction's outcome, the truster can be more certain of its experience-based model as more transaction observations contribute to it. This section explores the relationship between the number of transaction observations composing an experience-based trust model and the expected error of that model. Further, this section examines how a truster's reliance on experience- vs. reputation-based trust models (in terms of the Adaptive Trust Modeling technique proposed in Section 3.1) varies depending on the number of transactions the truster has observed. Intuitively, a truster is more likely to rely on its experience-based trust model when it has observed numerous outcomes of transactions with the trustee in question, making the experience-based model very certain; this section explains this correlation quantitatively.

A truster may use any number of techniques for combining transaction observations to form its experience-based trust model, such as trend extrapolation, averaging, or outlier removal, for example. Because the truster knows its own modeling technique, it can predict how the inclusion of additional observations will change subsequent suggestions derived from the model. As a result, the level of uncertainty of an experience-based model can be directly linked to the number of transaction observations of which it is composed. Section 3.1.4 demonstrates that in Adaptive Trust Modeling, weighting of trust models—in particular, experience- vs. reputation-based models—is related to the accuracy of each model (models with lower suggestion variation, σ_{sug} are given greater weight). This section explores how the accuracy of an experience-based model is calculated based on knowing the model's suggestion-calculating algorithm and number of transaction observations influencing the model, since an experience-based model changes in a predictable way, decreasing $\sigma_{E,sug}$ with each additional transaction observation.

To demonstrate this relationship between model error and number of transaction observations, an example scenario is illustrated using the following assumptions. Assuming a consistent trustee behavior distribution $N(\mu_{beh}, \sigma_{beh})$, (this assumption is relaxed in Section 3.2.3), let m represent the number of transaction observations upon which the experience-based model is calculated. Assume the experience-based model is built as described previously in Section 3.1.3, where a suggestion is calculated as

$$P_{E,sug}(m) = \frac{\sum_{i=1}^{m} \chi_{t(i)} P_{act,i}}{\sum_{i=1}^{m} \chi_{t(i)}} \qquad \text{Eqn 2}$$

and observed transaction outcomes are weighted according to the following equation:

$$\chi_t = \frac{\chi_0}{(t+1)^{\alpha}}. \qquad \text{Eqn 3}$$

Figure 3-10 shows weights χ_t as observation age t increases for several values of α: 0, 1, 2, and 3. When $\alpha = 0$, all observations, regardless of age, are weighted equally. As α increases, the influence of older observations decreases more quickly.

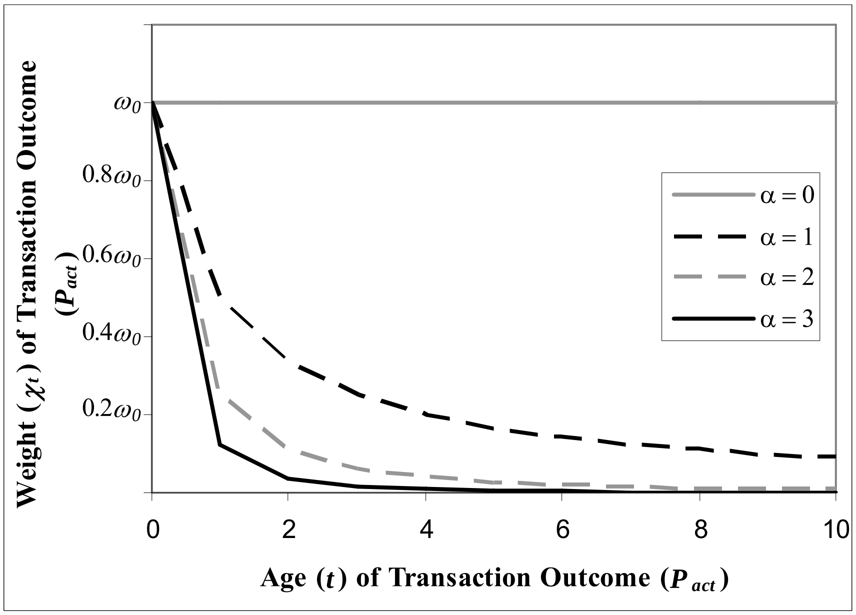


Figure 3-10. Experience-based suggestion weight (χ_t) as a function of suggestion age (τ) for α values of 0, 1, 2, and 3. Solid lines are for clarity only (τ is discrete).

Since each observed transaction outcome $P_{act,i}$ belongs to the distribution $N(\mu_{beh}, \sigma_{beh})$, then an individual suggestion, $P_{E,sug}(m)$, based on m observations, follows the distribution $N(\mu_{E,sug}(m), \sigma_{E,sug}(m))$ where

$$\mu_{E,sug}(m) = \frac{\sum_{i=1}^{m} \chi_{t(i)} \mu_{beh}}{\sum_{i=1}^{m} \chi_{t(i)}} = \mu_{beh} \text{ and} \qquad \text{Eqn 21}$$

$$\sigma_{E,sug}(m) = \frac{\sqrt{\sum_{i=1}^{m} \left(\chi_{t(i)} \sigma_{beh}\right)^2}}{\sum_{i=1}^{m} \chi_{t(i)}}. \qquad \text{Eqn 22}$$

Assuming one transaction observation occurs at each discrete timestep, Equation 22 is expanded using Equation 3,

$$\sigma_{E,sug}(m)=\frac{\sqrt{\left(\chi_{t(0)}\sigma_{beh}\right)^2+\left(\chi_{t(1)}\sigma_{beh}\right)^2+\ldots+\left(\chi_{t(m)}\sigma_{beh}\right)^2}}{\chi_{t(0)}+\chi_{t(1)}+\ldots+\chi_{t(m)}}$$

$$\sigma_{E,sug}(m)=\frac{\sqrt{\left(\frac{\chi_0}{\left((0)+1\right)^{\alpha}}\sigma_{beh}\right)^2+\left(\frac{\chi_0}{\left((1)+1\right)^{\alpha}}\sigma_{beh}\right)^2+\ldots+\left(\frac{\chi_0}{\left((m-1)+1\right)^{\alpha}}\sigma_{beh}\right)^2}}{\frac{\chi_0}{\left((0)+1\right)^{\alpha}}+\frac{\chi_0}{\left((1)+1\right)^{\alpha}}+\ldots+\frac{\chi_0}{\left((m-1)+1\right)^{\alpha}}}$$

$$\sigma_{E,sug}(m)=\frac{\sqrt{\left(\frac{\chi_0}{1^{\alpha}}\sigma_{beh}\right)^2+\left(\frac{\chi_0}{2^{\alpha}}\sigma_{beh}\right)^2+\ldots+\left(\frac{\chi_0}{m^{\alpha}}\sigma_{beh}\right)^2}}{\frac{\chi_0}{1^{\alpha}}+\frac{\chi_0}{2^{\alpha}}+\ldots+\frac{\chi_0}{m^{\alpha}}}$$

$$\sigma_{E,sug}(m)=\frac{\chi_0\sigma_{beh}\sqrt{\left(\frac{1}{1^{\alpha}}\right)^2+\left(\frac{1}{2^{\alpha}}\right)^2+\ldots+\left(\frac{1}{m^{\alpha}}\right)^2}}{\chi_0\left(\frac{1}{1^{\alpha}}+\frac{1}{2^{\alpha}}+\ldots+\frac{1}{m^{\alpha}}\right)}$$

$$\sigma_{E,sug}(m)=\frac{\sigma_{beh}\sqrt{\frac{1}{1^{2\alpha}}+\frac{1}{2^{2\alpha}}+\ldots+\frac{1}{m^{2\alpha}}}}{\frac{1}{1^{\alpha}}+\frac{1}{2^{\alpha}}+\ldots+\frac{1}{m^{\alpha}}}. \qquad \text{Eqn 23}$$

Figure 3-11 shows $\sigma_{E,sug}$ as a function of number of observed transaction outcomes *m* (assuming trustee behavior distribution remains constant) for several values of α: 0, 1, 2, and 3. When α = 0, $\sigma_{E,sug}$ decreases most quickly, resulting in lowest experience-based model error. However, α values greater than zero are advantageous in real situations when trustee behavior distributions may change over time, rendering older transaction observations obsolete. The system designer must determine the appropriate α for a given domain to both "exploit" minimum possible error (α = 0) and "explore" to identify changes in trustee behavior. Setting α = 0 is acceptable at this point, assuming the trustee's behavior follows a consistent distribution $N(\mu_{beh}, \sigma_{beh})$, since the time at which observations take place is inconsequential. Section 3.2.3 addresses the scenario in which trustee behavior distributions (μ_{beh} and/or σ_{beh}) change over time.

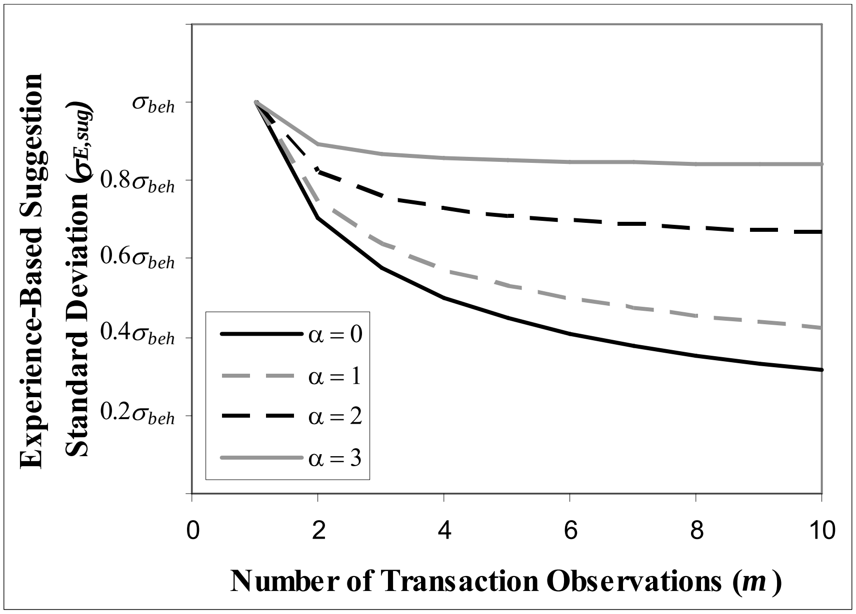


Figure 3-11. Experience-based suggestion standard deviation ($\sigma_{E,sug}$) as a function of number of transaction observations (*m*) for α values of 0, 1, 2, and 3. Solid lines are for clarity only (*m* is discrete).

Equation 23 is simplified when $\alpha = 0$:

$$\sigma_{E,sug}(m) = \frac{\sigma_{beh}\sqrt{\frac{1}{1^{2(0)}} + \frac{1}{2^{2(0)}} + \ldots + \frac{1}{m^{2(0)}}}}{\frac{1}{1^0} + \frac{1}{2^0} + \ldots + \frac{1}{m^0}}$$

$$\sigma_{E,sug}(m) = \frac{\sigma_{beh}\sqrt{\frac{1}{1} + \frac{1}{1} + \ldots + \frac{1}{1}}}{\frac{1}{1} + \frac{1}{1} + \ldots + \frac{1}{1}}$$

$$\sigma_{E,sug}(m) = \frac{\sigma_{beh}\sqrt{m}}{m}$$

$$\sigma_{E,sug}(m) = \frac{\sigma_{beh}}{\sqrt{m}} \qquad \text{Eqn 24}$$

Figure 3-12 illustrates the distribution $N(\mu_{E,sug}(m), \sigma_{E,sug}(m))$ for increasing values of *m* when $\alpha = 0$. As the number of observations (*m*) increases, $\sigma_{E,sug}(m)$—and expected suggestion error—decreases (the likelihood that the resulting suggestion $P_{E,sug}$ is near μ_{beh} increases). Because $\mu_{E,sug}(m)$ equals μ_{beh} for all m, (from Equation 21) it is asserted that experience-based models do not have error of distribution mean; the assumption in Section 3.1.4 that $\mu_{sug} = \mu_{beh}$ is not restrictive in the case of experience-based models.

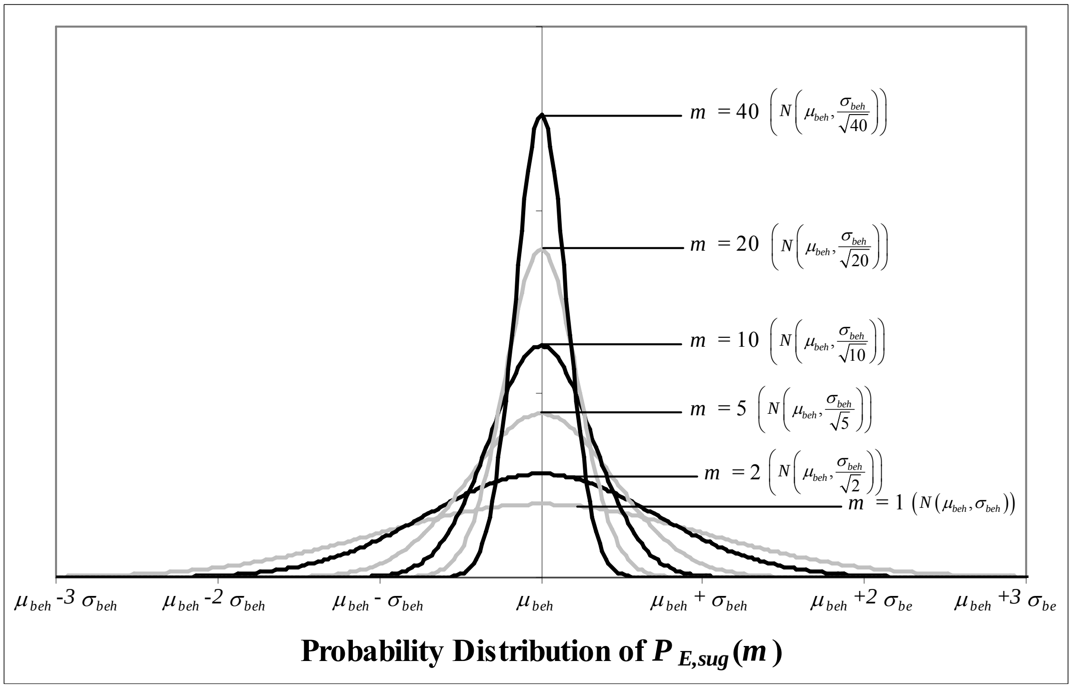


Figure 3-12. Probability distribution $N(\mu_{E,sug}(m)\ ,\ \sigma_{E,sug}(m))$ of experience-based suggestions $P_{E,sug}(m)$ for increasing values of m (number of observed transactions).

Standard deviation $\sigma_{E,sug}(m)$ correlates to the theoretical $\sigma_{E,sug}$ of Equations 13 and 14 in Section 3.1.4 needed to calculate weights $\omega_{E,\sigma_{agg,err,min}}$ and $\omega_{R,\sigma_{agg,err,min}}$. Further, from Equation 5 in Section 3.1.4, the accuracy of an experience-based model, in terms of $\sigma_{E,err}$, is calculated as

$$\sigma_{E,err} = \sqrt{\sigma_{E,sug}^2 + \sigma_{beh}^2}$$

$$\sigma_{E,err} = \sqrt{\left(\frac{\sigma_{beh}}{\sqrt{m}}\right)^2 + \sigma_{beh}^2}$$

$$\sigma_{E,err} = \sqrt{\frac{\sigma_{beh}^2}{m} + \sigma_{beh}^2}$$

$$\sigma_{E,err} = \sigma_{beh}\sqrt{\frac{m+1}{m}} . \qquad \text{Eqn 25}$$

Figure 3-13 shows theoretical $\sigma_{E,err}$ as a function of m; the function approaches σ_{beh}, as m approaches ∞.

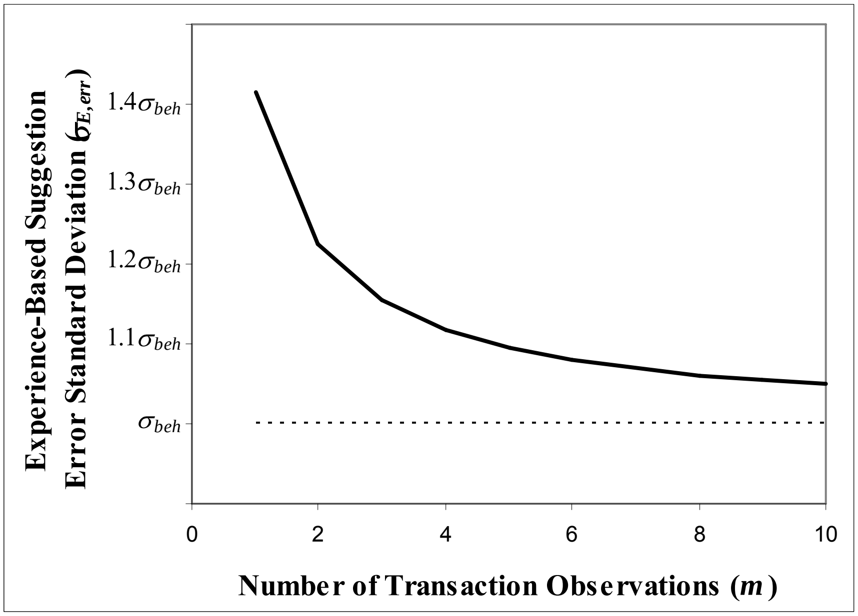


Figure 3-13 Theoretical experience-based model error standard deviation ($\sigma_{E,err}$) as a function of number of transaction observations (m). Trustee behavior standard deviation (σ_{beh}), the minimum achievable error, is shown as a baseline. Solid lines are for clarity only (m is discrete).

As m increases, appropriate weights for experience- vs. reputation-based models must be re-evaluated based on the accuracy of the truster's reputation-based model ($\sigma_{R,sug}$) and number of observations (m) influencing experience-based model suggestions. At this point in the research, reputation-based models are assumed to be simply some general aggregation of reputations (Section 3.3.2 addresses the formation of reputation-based trust models in detail). The weight, $\omega_{R,\sigma_{agg,err,min}}$, of the reputation-based model is computed, recalling Equation 13:

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\sigma_{E,sug}^2}{\sigma_{E,sug}^2 + \sigma_{R,sug}^2} .$$

Substituting Equation 24,

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\left(\frac{\sigma_{beh}}{\sqrt{m}}\right)^2}{\left(\frac{\sigma_{beh}}{\sqrt{m}}\right)^2 + \sigma_{R,sug}^2}$$

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\frac{\sigma_{beh}^2}{m}}{\frac{\sigma_{beh}^2}{m} + \sigma_{R,sug}^2}$$

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\sigma_{beh}^2}{\sigma_{beh}^2 + m\sigma_{R,sug}^2}. \qquad \text{Eqn 26}$$

Similarly, the weight of the experience-based model can be computed, recalling Equation 12:

$$\omega_E + \omega_R = 1$$

$$\omega_{E,\sigma_{agg,err,min}} = 1 - \frac{\sigma_{beh}^2}{\sigma_{beh}^2 + m\sigma_{R,sug}^2}$$

$$\omega_{E,\sigma_{agg,err,min}} = \frac{m\sigma_{R,sug}^2}{\sigma_{beh}^2 + m\sigma_{R,sug}^2}. \qquad \text{Eqn 27}$$

Note that Equation 25 is helpful for understanding how experience-based model error decreases theoretically as transactions are observed. In reality, however, a truster does not use Equation 25 to determine its experience-based model error standard deviation ($\sigma_{E,err}$), since the truster does not know σ_{beh} exactly (if it did, trust modeling itself—and suggestions $P_{E,sug}$ and $P_{R,sug}$ about trustee behavior—would be unnecessary). Instead, the truster estimates $\sigma_{E,err}$ by computing the standard deviation of actual experience-based suggestion errors ($P_{E,err}$), extended from Equation 4:

$$P_{E,err} = P_{E,sug} - P_{act}.$$

Similarly, the truster does not compute $\omega_{E,\sigma_{agg,err,min}}$ and $\omega_{R,\sigma_{agg,err,min}}$ from Equations 26 and 27, but from Equations 13 and 14, based on actual calculations of $\sigma_{E,sug}$, the standard deviation of P_{act} values.

Figure 3-14 shows theoretical $\omega_{E,\sigma_{agg,err,min}}$ as a function of m for several values of $\sigma_{R,sug}$ when $\sigma_{beh} = 1.0$. When $\sigma_{R,sug}$ is large compared to σ_{beh} (the reputation-based model is very inaccurate), $\omega_{E,\sigma_{agg,err,min}}$ increases quickly as m increases; the accuracy of the experience-based model quickly overshadows that of the inaccurate reputation-based model. Conversely, when $\sigma_{R,sug}$ is small compared to σ_{beh} (the reputation-based model is very accurate), $\omega_{E,\sigma_{agg,err,min}}$ increases slowly as m increases; the reputation-based model is a more accurate model, even when the experience-based model is based on many observations.

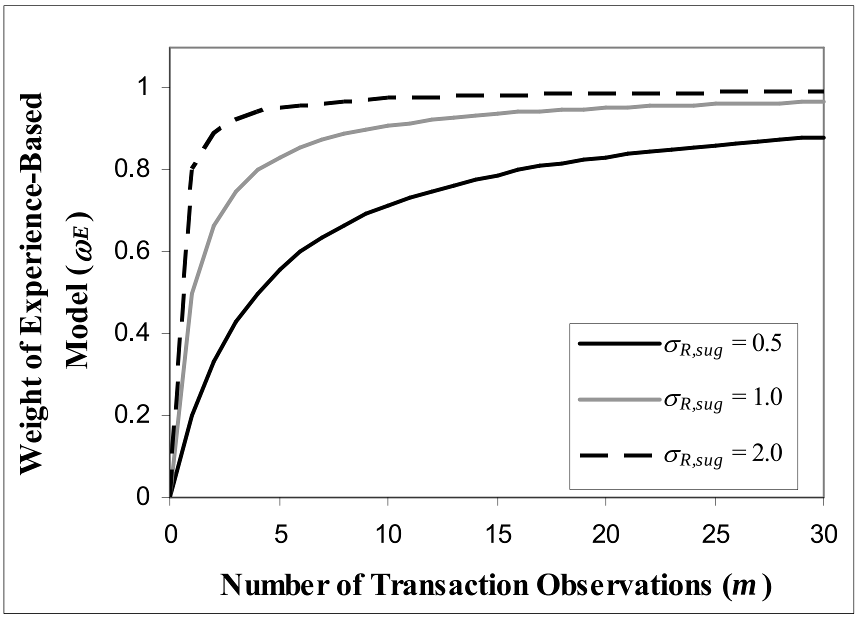


Figure 3-14. Adaptive Trust Modeling's theoretical weight (ω_E) of experience-based model as a function of number of transaction observations (m) when $\sigma_{R,sug}$ equals 0.5, 1.0, and 2.0 (σ_{beh} = 1.0). Solid lines are for clarity only (m is discrete).

The advantages of Adaptive Trust Modeling are demonstrated by Figure 3-15, which theoretically compares $\sigma_{agg,err}$ as the number of transaction observations, m, increases for four different weighting techniques as listed in Table 3-1: 1) Experience-Based Model Only, 2) Reputation-Based Model Only ($\sigma_{R,sug}$ equals 0.5), 3) Simple Averaging, and 4) Adaptive Trust Modeling.

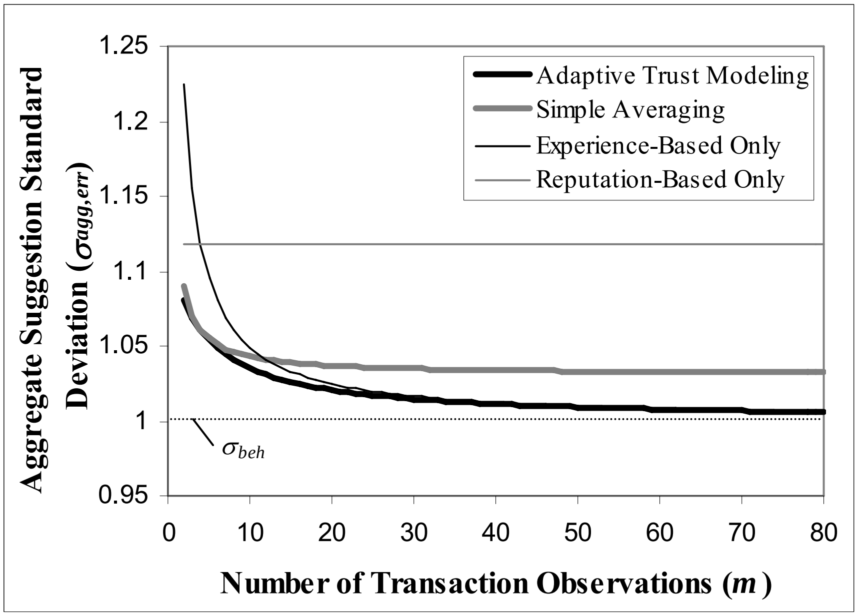


Figure 3-15. Theoretical comparison of aggregate suggestion error standard deviation ($\sigma_{agg,err}$) for Experience-Based Model Only, Reputation-Based Model Only, Simple Averaging, and Adaptive Trust Modeling techniques as number of transaction observations (m) increases ($\sigma_{R,sug}$ = 0.5). Trustee behavior standard deviation (σ_{beh} = 1.0), the minimum achievable error, is shown as a baseline. Solid lines are for clarity only (m is discrete).

Table 3-1. Weighting technique names, corresponding weights (ω_E and ω_R), and equations for aggregate error standard deviation ($\sigma_{agg,err}$).

Weighing Technique	Weights (ω_E, ω_R)	Aggregate Error Standard Deviation ($\sigma_{agg,err}$)
Experience-Based Model Only	$\omega_R = 0$ $\omega_E = 1$	$\sigma_{agg,err} = \sqrt{\sigma_{E,sug}^2 + \sigma_{beh}^2}$ (Eqn 5)
Reputation-Based Model Only	$\omega_R = 1$ $\omega_E = 0$	$\sigma_{agg,err} = \sqrt{\sigma_{R,sug}^2 + \sigma_{beh}^2}$ (Eqn 5)
Simple Averaging	$\omega_R = 0.5$ $\omega_E = 0.5$	$\sigma_{agg,err} = \sqrt{\left(0.5\sigma_{E,sug}\right)^2 + \left(0.5\sigma_{R,sug}\right)^2 + \sigma_{beh}^2}$ (Eqn 20)
Adaptive Trust Modeling	$\omega_R = \frac{\sigma_{E,sug}^2}{\sigma_{E,sug}^2 + \sigma_{R,sug}^2}$ $\omega_E = \frac{\sigma_{R,sug}^2}{\sigma_{E,sug}^2 + \sigma_{R,sug}^2}$	$\sigma_{agg,err} = \sqrt{\frac{\sigma_{E,sug}^2 \sigma_{R,sug}^2}{\sigma_{E,sug}^2 + \sigma_{R,sug}^2} + \sigma_{beh}^2}$ (Eqn 19)

As a baseline, Figure 3-15 also displays σ_{beh}, the minimum achievable error (achievable when 1) $\mu_{E,sug}$ and/or $\mu_{R,sug}$ equal μ_{beh}, and 2) $\sigma_{E,sug}$ and/or $\sigma_{R,sug}$ equal zero, depending one which model's suggestions are utilized). Based on Equation 19 in Table 3-1 and Equation 24, Adaptive Trust Modeling's aggregate error standard deviation, $\sigma_{agg,err}$, in terms of m, is expressed as

$$\sigma_{agg,err}(m) = \sqrt{\frac{\left(\frac{\sigma_{beh}^2}{m}\right)\sigma_{R,sug}^2}{\left(\frac{\sigma_{beh}^2}{m}\right)+\sigma_{R,sug}^2}+\sigma_{beh}^2}$$

$$\sigma_{agg,err}(m) = \sqrt{\frac{\sigma_{beh}^2\sigma_{R,sug}^2}{\sigma_{beh}^2+m\sigma_{R,sug}^2}+\sigma_{beh}^2}\ .$$

With few transaction observations (m is small), the $\sigma_{agg,err}$ for the experience-based model is high. However, after many observations (m is large), the $\sigma_{agg,err}$ for the experience-based model approaches the minimum possible error, σ_{beh}. By relying on reputation-based suggestions initially, then on experience-based suggestions as the experience-based model improves, Adaptive Trust Modeling achieves the lowest $\sigma_{agg,err}$ of all four techniques, approaching σ_{beh} as $m \rightarrow \infty$. Note that when experience- and reputation-based models have the same accuracy (that is, $\sigma_{E,err} = \sigma_{R,err}$), the Simple Averaging technique achieves $\sigma_{agg,err}$ as low as Adaptive Trust Modeling (because optimal weights for $\sigma_{agg,err,min}$ happen to be $\omega_R = \omega_E = 0.5$).

Experimentation reinforces the above theoretical calculations, validating Adaptive Trust Modeling and the assumption that empirical model error standard deviations, $\sigma_{E,err}$ and $\sigma_{R,err}$ (or model suggestion standard deviations, $\sigma_{E,sug}$ and $\sigma_{R,sug}$) are adequate bases for computing model weights. To confirm Figure 3-15, an experiment is conducted to compare error of aggregate suggestions using each of the four techniques described in Table 3-1: 1) Experience-Based Model Only, 2) Reputation-Based Model Only, 3) Simple Averaging, and 4) Adaptive Trust Modeling (all four techniques utilize only reputations regarding the initial transaction, when no experience-based model is available). In the experiment, a single truster has access to an aggregated reputation-based trust model which produces suggestions from the distribution $N(\mu_{R,sug} = \mu_{beh}, \sigma_{R,sug} = 0.5)$ (for this experiment, the truster is not concerned with how the reputations are selected and combined). The potential trustee behaves in such a manner that the truster's net payoff, P_{act}, follows the distribution $N(\mu_{beh} = 10, \sigma_{beh} = 1.0)$. Trustee behavior distribution mean, μ_{beh}, is a high positive value to ensure the truster does not decline transactions, slowing the rate at which transaction observations are acquired and m increases (Section 3.2.2 discusses the impact of trustee untrustworthiness on $\omega_{E,\sigma_{agg,err,min}}$ in greater depth). Each run consists of 100 transaction opportunities; results from n = 100,000 runs are averaged. For each of the four techniques compared, the absolute value error of the truster's aggregate suggestion is measured as the number of observed transactions, m, increases:

$$\textit{average absolute value error}(m) = \frac{\sum_{i=1}^{n} \left| P_{agg,sug,i}(m) - P_{act,i}(m) \right|}{n} \qquad \text{Eqn 28}$$

Note that the relationship between a normal error distribution given by $N(\mu_{agg,err} = 0, \sigma_{agg,err}(m))$ and the average absolute value error of values taken from that distribution is given by

$$\textit{average absolute value error}(m) = \sigma_{agg,err}(m)\sqrt{\frac{2}{\pi}} \qquad \text{Eqn 29}$$

[Fullam, 2003].

Within the experiment, the truster employs the following Adaptive Trust Modeling algorithm to compute aggregate suggestions $P_{agg,sug}$. In each timestep, the reputation-based model delivers a suggestion from the distribution $N(\mu_{R,sug}, \sigma_{R,sug})$. The truster computes a suggestion from its experience-based trust model as:

$$P_{E,sug} = \frac{\sum_{i=1}^{m} \chi_i P_{act,i}}{\sum_{i=1}^{m} \chi_i} \qquad \text{Eqn 2}$$

where $\chi_i = \frac{1}{m}$ for all i. Based on the previously calculated expected error of both the experience- and reputation-based trust models ($\sigma_{E,err}$ and $\sigma_{R,err}$, respectively), the truster computes weights, $\omega_{E,\sigma_{agg,err,min}}$ and $\omega_{R,\sigma_{agg,err,min}}$, for the two suggestions (from Equations 13 and 14 in Chapter 3):

$$\omega_{E,\sigma_{agg,err,min}} = \frac{\sigma^2_{R,sug}}{\sigma^2_{E,sug} + \sigma^2_{R,sug}} \text{ and} \qquad \text{Eqn 14}$$

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\sigma^2_{E,sug}}{\sigma^2_{E,sug} + \sigma^2_{R,sug}}. \qquad \text{Eqn 13}$$

If the experience-based suggestion is null (no transaction outcomes have been observed, $m = 0$), $\sigma_{E,sug}$ is assumed to be ∞; therefore, $\omega_{E,\sigma_{agg,err,min}} = 0$ and $\omega_{R,\sigma_{agg,err,min}} = 1$.

The aggregate suggestion, $P_{agg,sug}$, is computed as

$$P_{agg,sug} = \left(\omega_{E,\sigma_{agg,err,min}} P_{E,sug}\right) + \left(\omega_{R,\sigma_{agg,err,min}} P_{R,sug}\right),$$

remembering that weights for the experience- and reputation-based suggestions sum to one. If $P_{agg,sug}$ is greater than zero, the truster chooses to trust (the transaction occurs). If $P_{agg,sug}$ is less than or equal to zero, the truster declines to conduct the transaction. Upon observing the outcome of the transaction, the truster computes suggestion error ($P_{E,err}$ and $P_{R,err}$) from Equation 4 (Section 3.1.4) as

$$P_{E,err} = P_{E,sug} - P_{act} \text{ and}$$
$$P_{R,err} = P_{R,sug} - P_{act}.$$

$P_{E,err}$, $P_{R,err}$, $P_{E,sug}$, and $P_{R,sug}$ are used to update error and suggestion distributions for both experience- and reputation-based trust models, and then the process is repeated for the next transaction opportunity.

Results shown in Figure 3-16, comparing average absolute value error of aggregate suggestions for Experience-Based Model Only, Reputation-Based Model Only, Simple Averaging, and Adaptive Trust Modeling techniques, closely resemble the theoretical plot of $\sigma_{agg,err}$ in Figure 3-15. As m—and the accuracy of the experience-based model—increases, the error of the experience-based-only technique decreases. Adaptive Trust Modeling yields $\sigma_{agg,err}$ similar to or lower than all three other techniques for all values of m, both early on (low m) and after numerous transactions have been observed (high m). Adaptive Trust Modeling's error is statistically similar ($\alpha = 0.05$) to that of Simple Averaging when m is low, because $\omega_{E,\sigma_{agg,err,min}}$, as selected by Adaptive Trust Modeling, is close to 0.5, the weight used by Simple Averaging. When m is large, Adaptive Trust Modeling's error is statistically similar to that of Experience-Only, but significantly lower than that of Simple Averaging. Figure 3-17 shows the experiment's average experience-based model weight $\omega_{E,\sigma_{agg,err,min}}$ selected by the truster, as compared to the theoretical best weight from Figure 3-14, as a function of number of observed transactions m. Experimental and theoretical weights differ slightly because the truster's error estimates of experience- and reputation-based trust models are inexact, in reality. Weight $\omega_{E,\sigma_{agg,err,min}}$ increases as the accuracy of the experience-based model increases, in agreement with Figure 3-14.

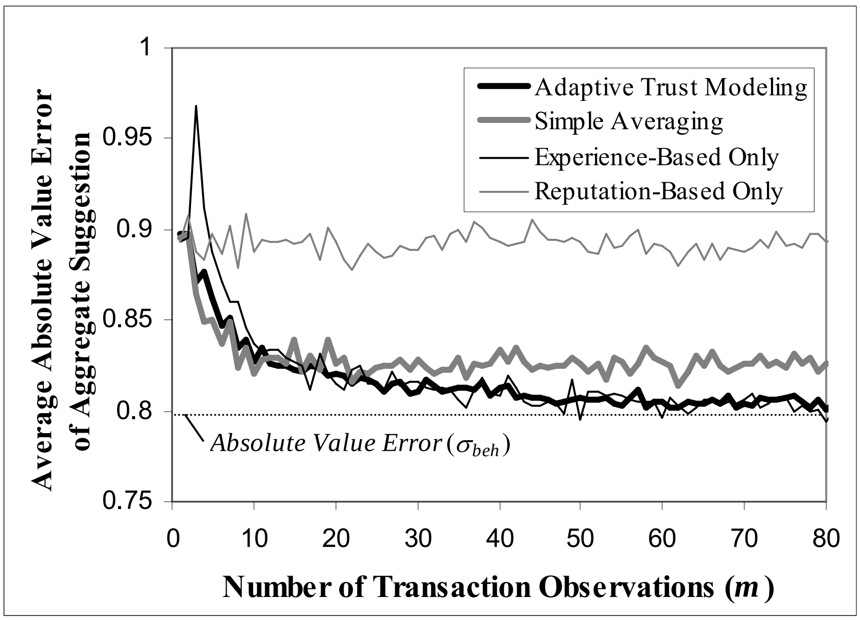


Figure 3-16. Experimental comparison of aggregate suggestion absolute value error for Experience-Based Model Only, Reputation-Based Model Only, Simple Averaging, and Adaptive Trust Modeling techniques as number of transaction observations (m) increases ($\sigma_{R,sug}$ = 0.5). Absolute value error for trustee behavior (σ_{beh} = 1.0), the minimum achievable error, is shown as a baseline. Solid lines are for clarity only (m is discrete).

In summary, the accuracy of an experience-based model is directly related to the number of transaction observations composing that model. Adaptive Trust Modeling favors a truster's experience-based model as the number of observations increases, and the experience-based model is favored more quickly if the truster's reputation-based model (the alternative to the experience-based model) is inaccurate. Adaptive Trust Modeling determines the optimal weighting between experience and reputations, producing aggregated suggestions that are more accurate than Simple Averaging and either single (experience- or reputation-based) model alone.

This section refutes Misconception 1 from Section 1.4: *Large systems (with many trusters/trustees) always make experience-based modeling ineffective.* In truth, experience-based modeling is effective as long as a truster has numerous repeated opportunities to transact with each trustee it considers. Trusters who conduct large numbers of transactions in large systems obtain enough transaction observations to make experience-based modeling useful; conversely, trusters who very rarely conduct any transactions, even in small systems, may have inaccurate experience-based models.

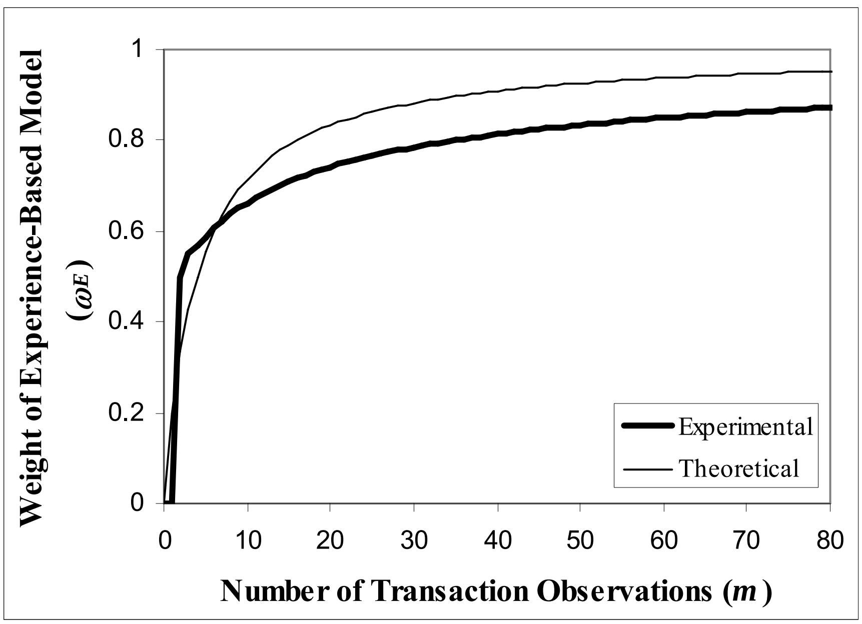


Figure 3-17. Comparison of Adaptive Trust Modeling's weight of the experience-based model ($\omega_{E,\sigma_{agg,err,min}}$) when computed theoretically versus measured experimentally as number of transaction observations (m) increases (σ_{beh} = 1.0, $\sigma_{R,sug}$ = 0.5). Solid lines are for clarity only (m is discrete).

Availability of transaction observations (more specifically, transactions predicted to yield a positive payoff) is limited when the potential trustee is perceived to be untrustworthy; the effect of trustee trustworthiness on a truster's ability to build its experience-based model is examined in Section 3.2.2. Further, when a trustee changes its behavior pattern, the truster's experience-based model, based on the earlier behavior pattern, becomes obsolete. In this case, the truster may be limited in the number of transaction observations it can acquire between trustee behavior changes; the impact of dynamic trustee behavior patterns on a truster's ability to build its experience-based model is examined in Section 3.2.3.

3.2.2 TRUSTEE BEHAVIOR: TRUSTWORTHY VS. UNTRUSTWORTHY

This section examines how a trustee's level of trustworthiness influences 1) a truster's ability to build an accurate experience-based trust model and 2) reliance on experience- vs. reputation-based trust models (as measured by weights using Adaptive Trust Modeling). Intuitively, a truster will rely on reputation-based models over experience-based models when a trustee is untrustworthy because the truster is less likely to observe enough transactions to build an accurate experience-based model. Alternatively, when a trustee is trustworthy, numerous transactions permit a truster to build an accurate experience-based model. This pattern is identifiable in real-world scenarios, such as auto repair; a smart consumer who has been previously cheated by an auto mechanic often seeks out numerous reputation recommendations, hesitating before trusting the mechanic again. Conversely, a consumer who has had positive experiences with an auto mechanic often quickly builds and relies on his own experiences, choosing to trust the mechanic repeatedly.

Two factors influence the relationship between trustee trustworthiness (as measured by μ_{beh}) and the weight the truster places on its experience-based trust model ($\omega_{E,\sigma_{agg,err,min}}$). First, the frequency of transactions affects how quickly the experience-based trust model is built; the less trustworthy a trustee is perceived by the truster to be (μ_{beh} is negative), the less likely transactions are to occur. Second, the accuracy of the truster's reputation-based model influences how many transaction observations are needed to make the truster's experience-based model more accurate that its reputation-based model.

Before a truster has observed any transactions with the trustee, it may base trusting decisions on only its reputation-based model, since no transactions have occurred upon which to base an experience-based model. When μ_{beh} is negative, there is a chance that the reputation-based model may suggest trusting; the probability of an incorrect suggestion to trust increases as $\sigma_{R,sug}$ is larger relative to the magnitude of μ_{beh}. When μ_{beh} is positive, the reputation-based model correctly suggests trusting (again, the probability of an incorrect suggestion increases with larger values of $\sigma_{R,sug}$). Each time the truster follows a suggestion to trust, it gains a transaction observation with which to build up its experience-based model. As the experience-based model is built up, the truster gives more weight to it ($\omega_{E,\sigma_{agg,err,min}}$ increases).

Frequency of transactions (or probability of a transaction occurring) is expressed by the ratio m/m_{opp}, where m_{opp} represents the number of transaction opportunities a truster encounters and m represents, from Section 3.2.1, the number of transactions the truster chooses to conduct (and upon which it bases its experience-based model). When μ_{beh} is negative, since transaction observations (and therefore, the truster's experience-based model) probabilistically indicate that the trustee is untrustworthy, the truster's aggregate suggestion is even less likely to suggest trusting, so even more transaction opportunities pass before another transaction occurs (m/m_{opp} decreases). When another transaction does occur, the additional transaction observation only reinforces that the truster should not trust; additionally, the truster places even more weight on the experience-based model, since it has acquired more transaction observations (in other words, m is larger). Therefore, a cycle forms in which the experience-based model is relied upon increasingly, yet experience-based suggestions indicate not to trust, which slows the rate at which the experience-based model is built up.

This experiment compares the weight, $\omega_{E,\sigma_{agg,err,min}}$, the truster places, when using Adaptive Trust Modeling, on its experience-based model (as opposed to reputation-based model) for different levels of trustee trustworthiness (defined by different μ_{beh} values). The setup for this experiment is similar to that of Section 3.2.1. A single truster has access to an aggregated reputation-based trust model with suggestions following the distribution $N(\mu_{R,sug}, \sigma_{R,sug})$, where $\mu_{R,sug} = \mu_{beh}$ and $\sigma_{R,sug}$ takes on values of 0.5 and 1.0. The trustee yields a payoff to the truster, P_{act}, according to the distribution $N(\mu_{beh}, \sigma_{beh})$, where μ_{beh} takes on values of -2.0, -1.0, -0.5, 0.0, 0.5, 1.0, and 2.0, and $\sigma_{beh} = 1.0$. Each run consists of 100 transaction opportunities (m_{opp}); results from n = 10,000 runs are averaged. Note that the truster utilizes only reputations regarding the initial transaction, when no experience-based model is available.

Figure 3-18 shows $\omega_{E,\sigma_{agg,err,min}}$ as a function of m_{opp} for several values of μ_{beh}, both negative (trustee is untrustworthy, overall) and positive (trustee is trustworthy, overall), when $\sigma_{R,sug}$ equals 0.5. When μ_{beh} equals -2.0, the likelihood of the reputation-based model suggesting "trust" is so small (because reputation suggestions follow the distribution $N(-2.0, 0.5)$), that the truster never chooses to trust the trustee. As a result, $\omega_{E,\sigma_{agg,err,min}}$ remains zero because the truster's experience-based trust model is never built (the ratio m/m_{opp} equals nearly zero), and the truster must continue to rely solely on its reputation-based trust model. When μ_{beh} equals -1.0, the likelihood of the reputation-based model suggesting "trust" is slightly greater (reputation suggestions follow the distribution $N(-1.0, 0.5)$). Therefore, the truster is more likely to trust occasionally, has more transaction opportunities to build up its experience-based trust model, and, therefore, becomes more favorable ($\omega_{E,\sigma_{agg,err,min}}$ increases) more quickly. When μ_{beh} equals -0.5, $\omega_{E,\sigma_{agg,err,min}}$ increases even more quickly for the same reason. In general, as negative values of μ_{beh} approach zero, the ratio m/m_{opp} increases, approaching 0.5.

When μ_{beh} is positive (0.5, 1.0, or 2.0), the reputation-based trust model (as well as the experience-based trust model, as it is built up) suggests trusting nearly always. Therefore, a transaction is observed at nearly every opportunity (the ratio m/m_{opp} approaches one as μ_{beh} increases). Further, as more transactions are observed, the truster's experience-based trust model is built up, reinforcing the positive suggestion to trust. As a result, $\omega_{E,\sigma_{agg,err,min}}$ increases more quickly when μ_{beh} is positive rather than negative, though $\omega_{E,\sigma_{agg,err,min}}$ increases only slightly more quickly when μ_{beh} equals 1.0 or 2.0 than when μ_{beh} equals 0.5.

Figure 3-19 shows $\omega_{E,\sigma_{agg,err,min}}$ as a function of m_{opp} for the same values of μ_{beh} when $\sigma_{R,sug}$ equals 1.0. When μ_{beh} is negative, the ratio m/m_{opp} is small; $\omega_{E,\sigma_{agg,err,min}}$ grows more slowly for more negative values of μ_{beh}. By examining Figure 3-18 and Figure 3-19, note that $\omega_{E,\sigma_{agg,err,min}}$ grows at a similar rate when μ_{beh} is negative for similar ratios of $\sigma_{R,sug}/\mu_{beh}$, which indicate similar probabilities of incorrect suggestions to trust (for example, compare μ_{beh} equals 1.0 in Figure 3-18, when $\sigma_{R,sug}$ equals 0.5, to μ_{beh} equals 2.0 in Figure 3-19, when $\sigma_{R,sug}$ equals 1.0). Especially when μ_{beh} is positive, $\omega_{E,\sigma_{agg,err,min}}$ grows more quickly in Figure 3-19 ($\sigma_{R,sug}$ equals 1.0) than in Figure 3-18 ($\sigma_{R,sug}$ equals 0.5) because the accuracy of the experience-based model more quickly outpaces the accuracy of the reputation-based model when the reputation-based model is less accurate.

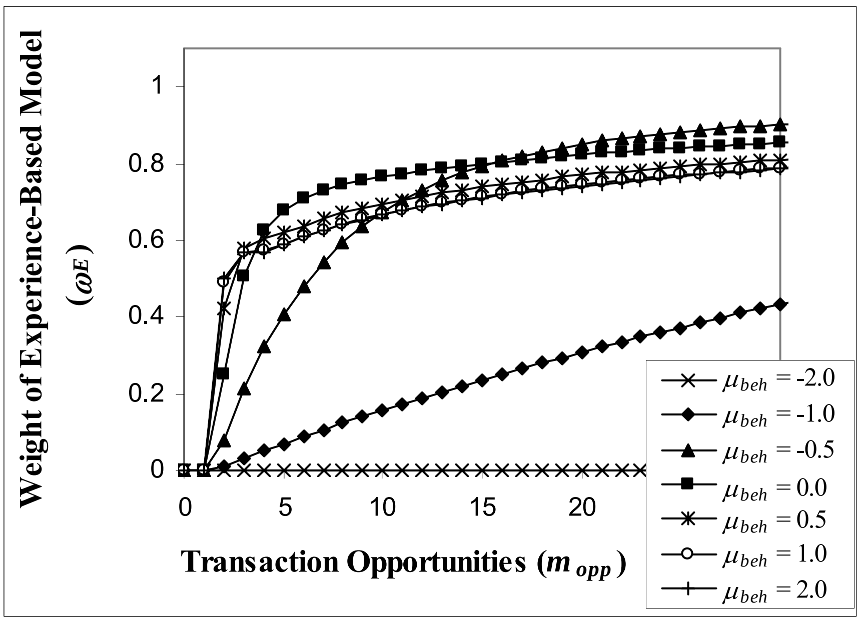


Figure 3-18. Adaptive Trust Modeling's weight (ω_E) of experience-based model as a function of number of transaction opportunities (m_{opp}) for the following values of μ_{beh}: -2.0, -1.0, -0.5, 0.0, 0.5, 1.0, and 2.0 (σ_{beh} = 1.0, $\sigma_{R,sug}$ = 0.5). Solid lines are for clarity only (m_{opp} is discrete).

In summary, trustee trustworthiness influences transaction frequency (m/m_{opp}), which determines how quickly experience-based trust model is built. A truster is less likely to conduct transactions with—and therefore, gain transaction observations about—an untrustworthy trustee. As a result, the truster's experience-based model takes longer (in terms of m_{opp}) to build and the truster relies more on its reputation-based model. Further, the increasingly-accurate experience-based model provides evidence of a trustee's level of trustworthiness, driving the truster to trust more (if the trustee is trustworthy) or less (untrustworthy), which either speeds or slows, respectively, further building of the experience-based trust model.

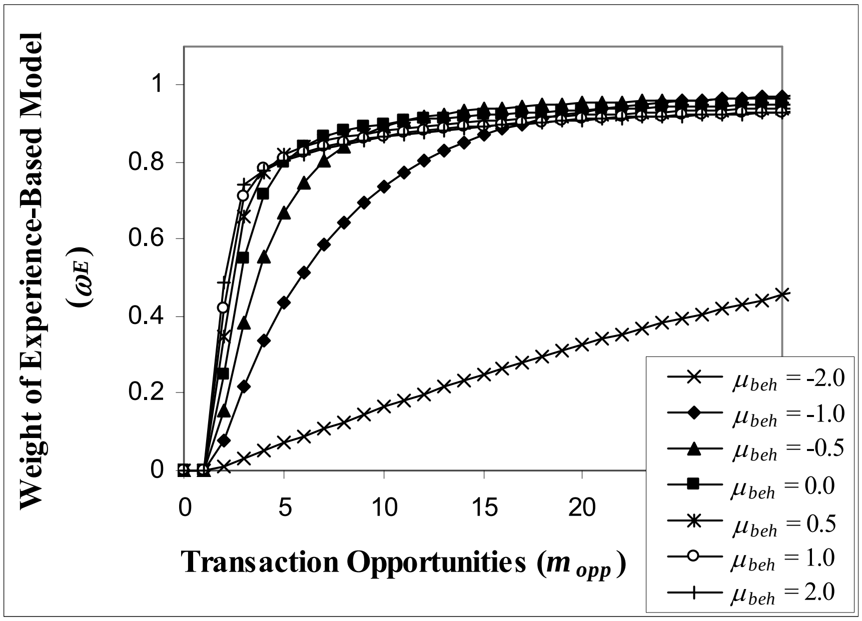


Figure 3-19. Adaptive Trust Modeling's weight (ω_E) of experience-based model as a function of number of transaction opportunities (m_{opp}) for the following values of μ_{beh}: -2.0, -1.0, -0.5, 0.0, 0.5, 1.0, and 2.0 (σ_{beh} = 1.0, $\sigma_{R,sug}$ = 1.0). Solid lines are for clarity only (m_{opp} is discrete).

3.2.3 Dynamic Trustee Trustworthiness

By relaxing the earlier assumption that a trustee's behavior distribution ($N(\mu_{beh}, \sigma_{beh})$) does not change, this section addresses how dynamic trustee trustworthiness influences a truster's experience-based trust model and reliance on experience- vs. reputation-based trust models. If trustee behavior changes frequently, the truster never observes enough transactions to build an accurate experience-based model. As a result, the truster is forced to always rely more on its reputation-based model. This intuitive result is seen often in real-world situations. For example, the quality of online businesses may change rapidly, with new companies starting up, going out of business, or building reliability. Customers who make infrequent purchases in these dynamic markets (such as eBay) repeatedly use reputation-based trust modeling—either through personal word-of-mouth or expert recommendations—before conducting repeat transactions. The rate at which past experiences (transaction observations) become obsolete is directly related to the rate at which the trustee changes its behavior [Fullam and Barber, 2005]. This concept is confirmed by the Nyquist-Shannon sampling theorem, which states that the transaction observation sampling rate must be at least twice the frequency at which the modeled behavior changes [Jerri, 1977].

Changes in trustee trustworthiness mean building an experience-based model must start anew and the number of observed transactions, *m*, is "reset" to zero (though it must be understood that the truster most likely does not know exactly when a change in the trustee's behavior pattern has occurred). Relationships between the frequency of trustee behavior changes (as measured by the number of observed transactions, *m*, that take place between each change) and resulting weights $\omega_{R,\sigma_{agg,err,min}}$ and $\omega_{E,\sigma_{agg,err,min}}$ are identified by the weight equations provided in Section 3.2.1:

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\sigma_{beh}^2}{\sigma_{beh}^2 + m\sigma_{R,sug}^2} \qquad \text{Eqn 26}$$

$$\omega_{E,\sigma_{agg,err,min}} = \frac{m\sigma_{R,sug}^2}{\sigma_{beh}^2 + m\sigma_{R,sug}^2}. \qquad \text{Eqn 27}$$

To determine the theoretical number of observed transactions necessary to build an experience-based model with accuracy such that a specific value for $\omega_{E,\sigma_{agg,err,min}}$ is achieved, Equation 27 is rearranged to solve for *m*:

$$\omega_{E,\sigma_{agg,err,min}} = \frac{m\sigma_{R,sug}^2}{\sigma_{beh}^2 + m\sigma_{R,sug}^2}$$

$$\omega_{E,\sigma_{agg,err,min}}\left(\sigma_{beh}^2 + m\sigma_{R,sug}^2\right) = m\sigma_{R,sug}^2$$

$$\sigma_{beh}^2\omega_{E,\sigma_{agg,err,min}} + m\sigma_{R,sug}^2\omega_{E,\sigma_{agg,err,min}} = m\sigma_{R,sug}^2$$

$$\sigma_{beh}^2\omega_{E,\sigma_{agg,err,min}} = m\sigma_{R,sug}^2 - m\sigma_{R,sug}^2\omega_{E,\sigma_{agg,err,min}}$$

$$\sigma_{beh}^2\omega_{E,\sigma_{agg,err,min}} = m\sigma_{R,sug}^2\left(1-\omega_{E,\sigma_{agg,err,min}}\right)$$

$$m = \frac{\sigma_{beh}^2\omega_{E,\sigma_{agg,err,min}}}{\sigma_{R,sug}^2\left(1-\omega_{E,\sigma_{agg,err,min}}\right)}. \qquad \text{Eqn 30}$$

In particular, to theoretically build an experience-based model with accuracy equivalent to that of a reputation-based trust model ($\omega_{E,\sigma_{agg,err,min}}$ = $\omega_{R,\sigma_{agg,err,min}}$ = 0.5), Equation 30 simplifies to:

$$m = \frac{\sigma_{beh}^2}{\sigma_{R,sug}^2}.$$

Therefore, the number of observed transactions needed to build an experience-based model at least as accurate as a given reputation-based model depends on both the accuracy of the reputation-based model ($\sigma_{R,sug}$) and the amount of variation in the trustee's behavior (σ_{beh}). If the trustee changes its behavior pattern more frequently than every $\frac{\sigma_{beh}^2}{\sigma_{R,sug}^2}$ transactions, the truster is likely to always favor its reputation-based model. If $\sigma_{R,sug}$ is very large compared to σ_{beh} (reputations are very inaccurate), the experience-based trust model requires only a few transaction observations to become more accurate than the reputation-based trust model. If $\sigma_{R,sug}$ is very small compared to σ_{beh} (reputation model is very accurate), then the reputation-based model will be trusted more than the experience-based model, even if the trustee changes its behavior rarely.

In the extreme case, the trustee may change behavior patterns randomly with each new observed transaction. In this case, m always equals zero, since the truster's experience-based trust model is obsolete after every observed transaction. Therefore, the theoretical best weight the truster should assign its experience-based model is given by:

$$\omega_{E,\sigma_{agg,err,min}} = \frac{m\sigma_{R,sug}^2}{\sigma_{beh}^2 + m\sigma_{R,sug}^2}$$

$$\omega_{E,\sigma_{agg,err,min}} = \frac{0 \cdot \sigma_{R,sug}^2}{\sigma_{beh}^2 + 0 \cdot \sigma_{R,sug}^2}$$

$$\omega_{E,\sigma_{agg,err,min}} = 0.$$

In other words, such high variability in the trustee's behavior yields the truster's experience-based trust model useless, and the truster is likely to always weight its reputation-based trust model as $\omega_{R,\sigma_{agg,err,min}} = 1$. In practice, however, if the trustee's behavior shifts follow a pattern, the experience-based model may build a model with a wider error distribution, encompassing both variation due to individual σ_{beh} values between each change, as well as the additional error due to the overall change pattern. In essence, patterns in trustee behavior shifts simply represent trustee behavior distributions with larger standard deviations. In these cases, the truster can substitute its estimates of model error standard deviation ($\sigma_{E,err}$ and $\sigma_{R,err}$) for estimates of suggestion standard deviation ($\sigma_{E,sug}$ and $\sigma_{R,sug}$) when computing weights, as is done in the experiments below.

These experiments demonstrate that the truster's experience-based trust model is less favored by Adaptive Trust Modeling ($\omega_{E,\sigma_{agg,err,min}}$ is lower) when the trustee changes its behavior pattern more frequently. Dynamic trustee behavior is modeled as changes in μ_{beh} (σ_{beh} remains constant at 1.0) according to a uniform distribution between 2.0 and 8.0 (all values of μ_{beh} remain positive to avoid large numbers of declined transactions, which cause the ratio m/m_{opp} to be less than one, from Section 3.2.2). Changes in μ_{beh} occur after every m_{max} transactions (m_{max} equals 1, 5, or 50). The truster is assumed to calculate its experience-based suggestion, $P_{E,sug}$, as described in Section 3.1.3:

$$P_{E,sug} = \frac{\sum_{i=1}^{m} \chi_i P_{act,i}}{\sum_{i=1}^{m} \chi_i} \qquad \text{Eqn 2}$$

with discrete discounting for age:

$$\chi(t) = \begin{cases} 1 \text{ for } 0 \le t \le \tau \\ 0 \text{ for } \tau < t \end{cases}$$

where τ equals five. Similarly, the five most recent reputation-based suggestions are used to compute the truster's estimate of $\sigma_{R,sug}$. Results from $n = 100$ runs are averaged for each experiment.

Figure 3-20, Figure 3-21, and Figure 3-22 show average absolute value error (calculated as in Equation 28 in Section 3.2.1) as a function of number of transaction observations (m) for three weighting techniques: 1) Experience-Based Model Only, 2) Reputation-Based Model Only, and 3) Adaptive Trust Modeling. All three techniques utilize reputations regarding the initial transaction, when no experience-based model is available. Reputation suggestions follow the distribution $N(\mu_{R,sug}, \sigma_{R,sug})$, where $\mu_{R,sug}$ equals μ_{beh} (which changes every m_{max} transactions) and $\sigma_{R,sug}$ equals 0.1. Since $\sigma_{R,sug}$

represents the variation in reputation suggestions for a single μ_{beh}, the actual distribution of all reputation suggestions, over all changes in μ_{beh}, is wider.

In Figure 3-20, m_{max} equals 50; trustee behavior, as indicated by μ_{beh}, shifts relatively infrequently. Though the error of the truster's experience-based model (as shown by the Experience-Based Model Only dataset) spikes immediately after shifts in μ_{beh}, many transaction observations occur between shifts, enabling the experience-based model to become as accurate as the reputation-based model (shown by the Reputation-Based Model Only dataset). The Adaptive Trust Modeling maintains error magnitudes close to but significantly (α = 0.05) higher than the Reputation-Based Model Only weighting technique, but significantly lower than the Experience-Based Model Only weighting technique, with slight spikes but immediate recovery at μ_{beh} shifts.

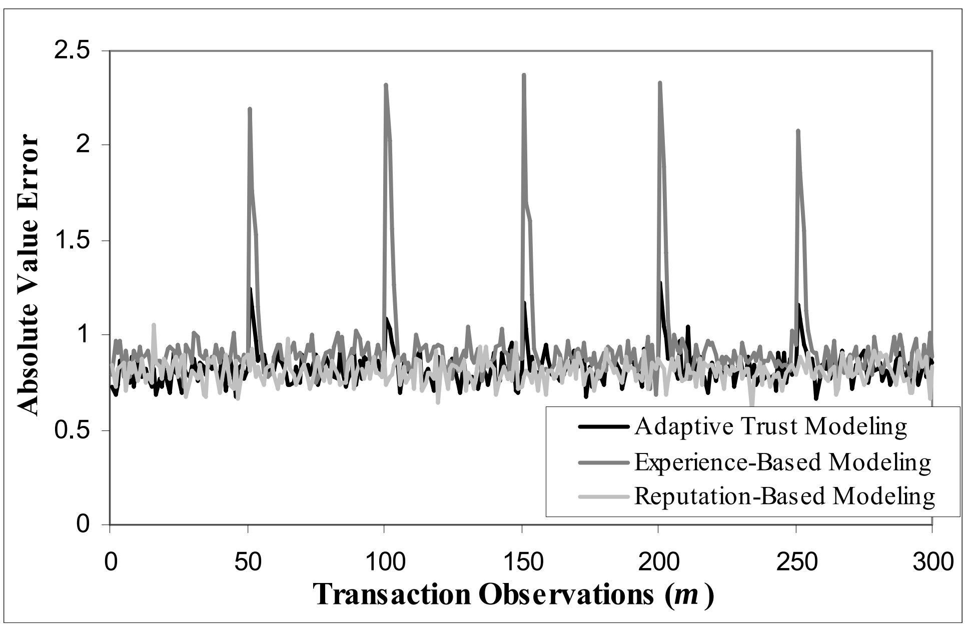


Figure 3-20. Absolute value error as a function of number of transaction observations m (σ_{beh} = 1.0, $\sigma_{R,sug}$ = 0.1, m_{max} equals 50, τ = 5). Three weighting techniques are shown: 1) Experience-Based Model Only, 2) Reputation-Based Model Only, and 3) Adaptive Trust Modeling. Solid lines are for clarity only (m is discrete).

In Figure 3-21, trustee behavior shifts more frequently (m_{max} equals 5). As a result, the experience-based model never observes enough transactions to achieve accuracy on par with the reputation-based model. Instead, the error of the experience-based model continually fluctuates, with just enough transaction observations between μ_{beh} shifts to achieve error near (yet still greater than) that of the reputation-based model before spiking again. The Adaptive Trust Modeling maintains error magnitudes close to but significantly (α = 0.05) higher than the Reputation-Based Model Only weighting technique, but significantly lower than the Experience-Based Model Only weighting technique.

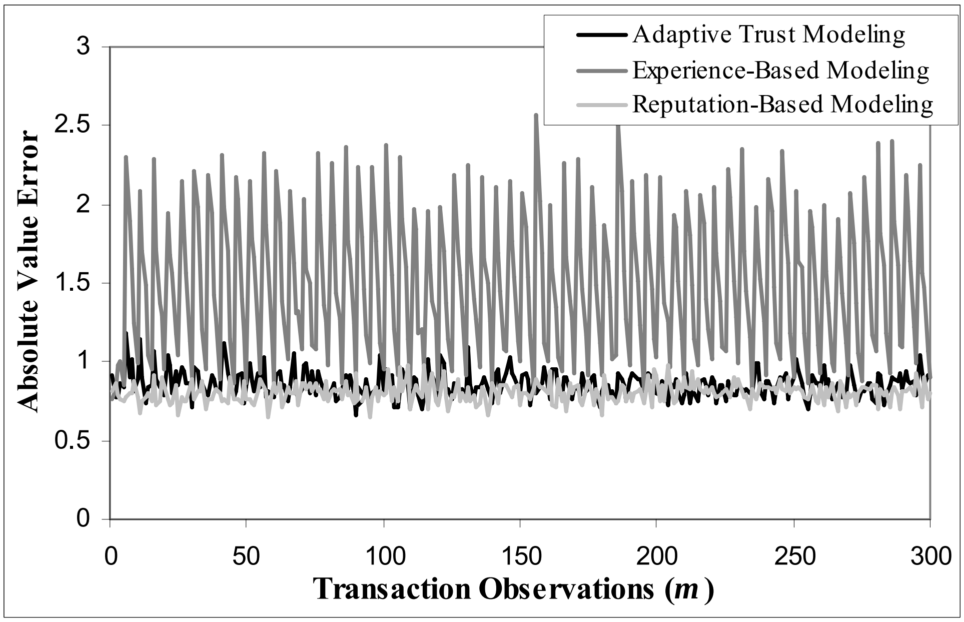


Figure 3-21. Absolute value error as a function of number of transaction observations m (σ_{beh} = 1.0, $\sigma_{R,sug}$ = 0.1, m_{max} equals 5, τ = 5). Three weighting techniques are shown: 1) Experience-Based Model Only, 2) Reputation-Based Model Only, and 3) Adaptive Trust Modeling. Solid lines are for clarity only (m is discrete).

In Figure 3-22, trustee behavior shifts continuously (m_{max} equals 1). As a result, the experience-based model is never built up. In fact, the experience-based model models what appears as a wider distribution: the trustee's distribution $N(\mu_{R,sug}, \sigma_{R,sug})$ compounded by μ_{beh} changes (according to $U(2.0, 8.0)$) after each observed transaction. Therefore, the experience-based model's error is much greater than that of that of the reputation-based model. Again, The Adaptive Trust Modeling maintains error magnitudes close to but significantly (α = 0.05) higher than the Reputation-Based Model Only weighting technique, but significantly lower than the Experience-Based Model Only weighting technique.

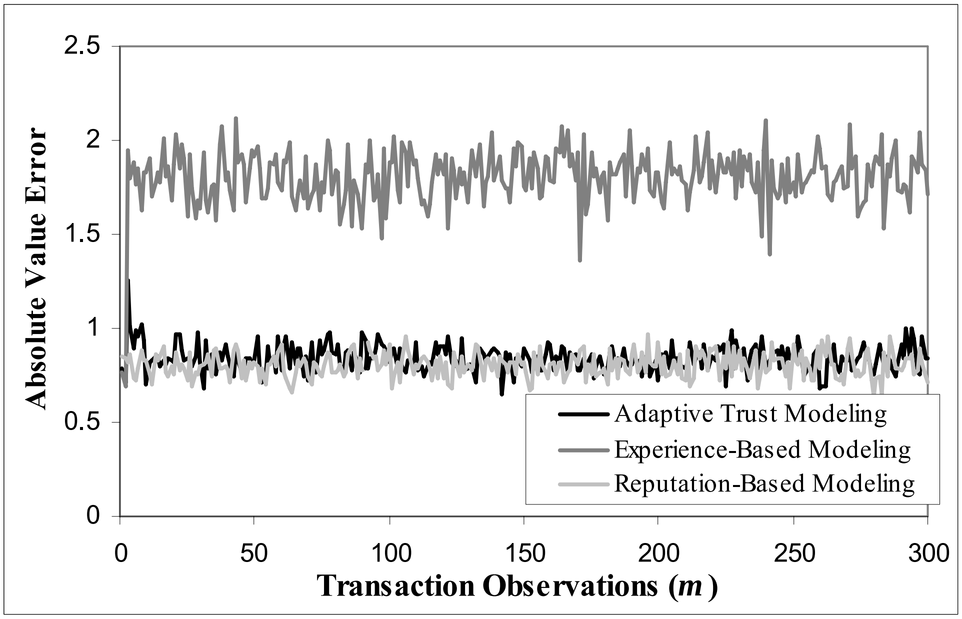


Figure 3-22. Absolute value error as a function of number of transaction observations m (σ_{beh} = 1.0, $\sigma_{R,sug}$ = 0.1, m_{max} equals 1, τ = 5). Three weighting techniques are shown: 1) Experience-Based Model Only, 2) Reputation-Based Model Only, and 3) Adaptive Trust Modeling. Solid lines are for clarity only (m is discrete).

Experience-based model weights ($\omega_{E,\sigma_{agg,err,min}}$) computed by Adaptive Trust Modeling are shown in Figure 3-23. When m_{max} equals 50, the truster weights its experience- and reputation-based models nearly equally: $\omega_{E,\sigma_{agg,err,min}}$ equals 0.4 (exact weights depend on specific values of σ_{beh} and $\sigma_{R,sug}$). When m_{max} equals 5, $\omega_{E,\sigma_{agg,err,min}}$ is lower (than when m_{max} equals 50)—decreasing early on before stabilizing at about 0.2—because the truster's experience-based model lacks enough transaction observations between μ_{beh} shifts to become as accurate as the reputation-based model. Finally, $\omega_{E,\sigma_{agg,err,min}}$ is lowest (0.15) when m_{max} equals 1, since the truster's experience-based model is never built up. However, $\omega_{E,\sigma_{agg,err,min}}$ does not reach zero because the experience-based model identifies the larger pattern of trustee behavior changes, building a model with larger error standard deviation. Exact $\omega_{E,\sigma_{agg,err,min}}$ values are also influenced by the τ value chosen by the designer. When τ is customized—low τ when m_{max} is low (to maximize exploration) and high τ when m_{max} is high (to maximize exploitation)—experimental

$\omega_{E,\sigma_{agg,err,min}}$ values are closer to the theoretical values given by Equation 27. Further, it is hypothesized that customization of τ enables Adaptive Trust Modeling to achieve error levels statistically similar to those of the Reputation-Based Model Only technique.

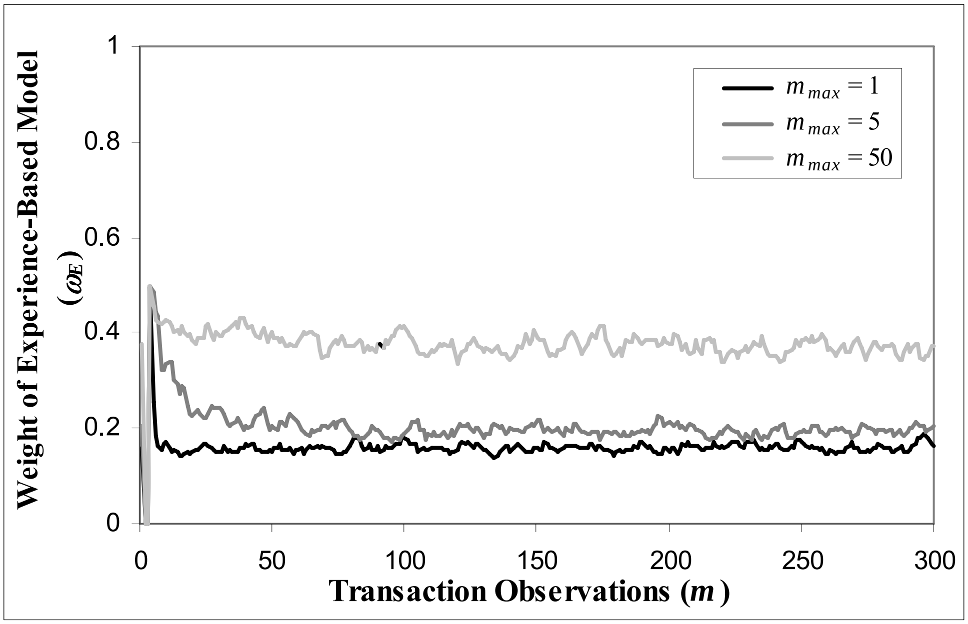


Figure 3-23. Adaptive Trust Modeling's weight (ω_E) of experience-based model as a function of number of transaction observations (m) for three values of m_{max}: 1, 5, and 50. Solid lines are for clarity only (m is discrete).

In summary, increased frequency of trustee behavior changes permits fewer transaction observations before an experience-based model is obsolete. As a result, reputation-based models prove more reliable when trustee trustworthiness is dynamic. Nevertheless, if trustee trustworthiness changes follow a pattern, an experience-based model may provide suggestions based on that wider-varying pattern. As a result, an experience-based model may provide useful suggestions when trustee trustworthiness is highly dynamic, but with greater error. Adaptive Trust Modeling determines the optimal weighting between experience and reputations, regardless of trustee trustworthiness dynamics, producing aggregated suggestions that are more accurate than either experience- or reputation-based modeling alone.

This section refutes Misconception 2 from Section 1.4: *Infrequent transactions always make experience-based modeling ineffective.* In truth, experience-based modeling is effective as long as the frequency with which transaction observations are accumulated sufficiently exceeds the frequency with which a trustee changes its trustworthiness behavior pattern. Infrequent transactions still build an effective experience-based model if trustee behavior patterns change so rarely that the truster can still obtain transaction observations between those changes.

3.3 Reputation-Based Trust Model Usability Factors

This section examines factors influencing the quality of reputation-based trust models, including the accuracy of reputations a truster receives and cost of acquiring reputations. Experiments in Section 3.3.1.1 demonstrate that the weight of a truster's reputation-based model, as computed by Adaptive Trust Modeling, is higher when the accuracy of that model is higher. Error-Sensitive Translation (Section 3.3.1.2) enables a truster to utilize consistent, though inaccurate ($\mu_{R,err} \neq 0$), suggestions from reputation providers, validating the statement in Section 3.1.4 that reputation error means are assumed to be zero. Finally, experiments in Section 3.3.1 demonstrate that the weight of a truster's reputation-based model is lower when reputation acquisition costs are high, since the number of reputations the truster can afford is more limited. These reputation cost experiments motivate Adaptive Cost Selection (Chapter 4), by which a truster assesses the value of trust information and determines the appropriate trust information to acquire, in light of acquisition costs.

3.3.1 Reputation-Based Model Accuracy

This section examines how the accuracy of a reputation-based model influences the usefulness of that model. Accuracy is examined both in terms of model error standard deviation (when model suggestions vary widely) and mean (when the model suggestions are consistent, yet incorrect). Two scenarios are considered: 1) the reputation-based model maintains constant accuracy and 2) the reputation-based model increases in accuracy over time.

3.3.1.1 Accuracy by Error Standard Deviation

This section explores how the usefulness of a reputation-based trust model varies depending on its error standard deviation. Two scenarios are examined: in the first, the reputation-based model maintains a constant error standard deviation, while in the second, the reputation-based model error standard deviation decreases over time. Reputation-based models with constant error standard deviation are more likely when reputation providers in the system are established and provide reputation suggestions of consistent accuracy. Reputation-based models with decreasing error standard deviation are more likely when reputation providers are improving their own trust models over time.

Experience-based models require more transaction observations (higher m) to match the accuracy of a highly-accurate reputation-based model, as opposed to an inaccurate reputation-based model. Therefore, reputation-based models with lower error standard deviations ($\sigma_{R,err}$) take "longer" (more transaction observations) to become outweighed by a truster's experience-based model. This relationship is consistent with real-world examples. When recommendations from others, such as experts, prove very reliable, humans tend to trust those experts more than their own experiences, even when their experience-based models are based on numerous transactions. On the contrary, when a recommendation is provided by a very unreliable source, a human truster will override those recommendations even with few experiences on which to rely. For example, a patient with a chronic illness may follow the advice of a world-renown expert, even if the patient has years of experience dealing with the illness himself. In contrast, the patient may discount the recommendations of a hurried clinic nurse, even about symptoms with which the patient is not familiar. The patient perceives the expert to be a much more accurate (reputation) provider than the nurse, and so trusts the expert's recommendations above the patient's own experience, but experience above the advice of the nurse.

Equation 26 in Section 3.1.2 describes the weight, $\omega_{R,\sigma_{agg,err,min}}$, of a reputation-based model in terms of the number of observed transactions, m, the variation in the trustees trustworthiness behavior, σ_{beh}, and the accuracy of the reputation-based model, as described by $\sigma_{R,sug}$:

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\sigma_{beh}^2}{\sigma_{beh}^2 + m\sigma_{R,sug}^2}. \qquad \text{Eqn 26}$$

Based on Equation 26, more accurate (lower $\sigma_{R,sug}$) reputation-based models are weighted more highly by Adaptive Trust Modeling for constant trustee behavior (σ_{beh}) and number of observed transactions (m).

This weight relationship is demonstrated by experiments, extending those in Section 3.2.1, which compare experience- vs. reputation-based trust models. This experiment compares the error of aggregate suggestions ($\sigma_{agg,err}$) using each of the four techniques described in Section 3.2.1: 1) Experience-Based Model Only, 2) Reputation-Based Model Only, 3) Simple Averaging, and 4) Adaptive Trust Modeling (all four techniques utilize only reputations regarding the initial transaction, when no experience-based model is available). A single truster has access to an aggregated reputation-based trust model which produces suggestions from the distribution $N(\mu_{R,sug}, \sigma_{R,sug})$, where $\mu_{R,sug} = \mu_{beh}$ and $\sigma_{R,sug}$ takes on a value of 0.0, 0.3, 0.5, or 1.0. The truster is not concerned with how the reputations are selected and combined to achieve the specified level of accuracy (selecting and combining reputations will be addressed in Section 3.2.2). The potential trustee behaves in such a manner that its payoff to the truster, P_{act}, follows the unchanging distribution $N(\mu_{beh} = 10, \sigma_{beh} = 1.0)$; as in Section 3.2.1, μ_{beh} is a high positive value to ensure the truster does not decline transactions, slowing the rate at which transaction observations are acquired and lowering the ratio m/m_{opp}. Each run consists of 100 transaction opportunities, and results from n = 100,000 runs are averaged.

Figure 3-24, Figure 3-25, Figure 3-26, and Figure 3-27 display absolute value error (as defined by Equation 28 in Section 3.2.1) as a function of number of observed transactions (m) when $\sigma_{R,sug}$ equals 0.0, 0.3, 0.5, and 1.0, respectively (note that Figure 3-26, in which $\sigma_{R,sug}$ equals 0.5, is identical to Figure 3-16 in Section 3.2.1). In all cases, the absolute value error yielded by the reputation-based model is consistent as m increases; higher $\sigma_{R,sug}$ results in higher absolute value error. When $\sigma_{R,sug}$ equals zero

(Figure 3-24), the reputation-based model provides the highest accuracy possible; therefore, it is not advantageous for the truster to utilize its experience-based model in this case. Adaptive Trust Modeling achieves error levels statistically similar (α = 0.05) to those of the reputation-based model once the truster quickly discovers the reputation-based model's high accuracy during the initial few transaction opportunities.

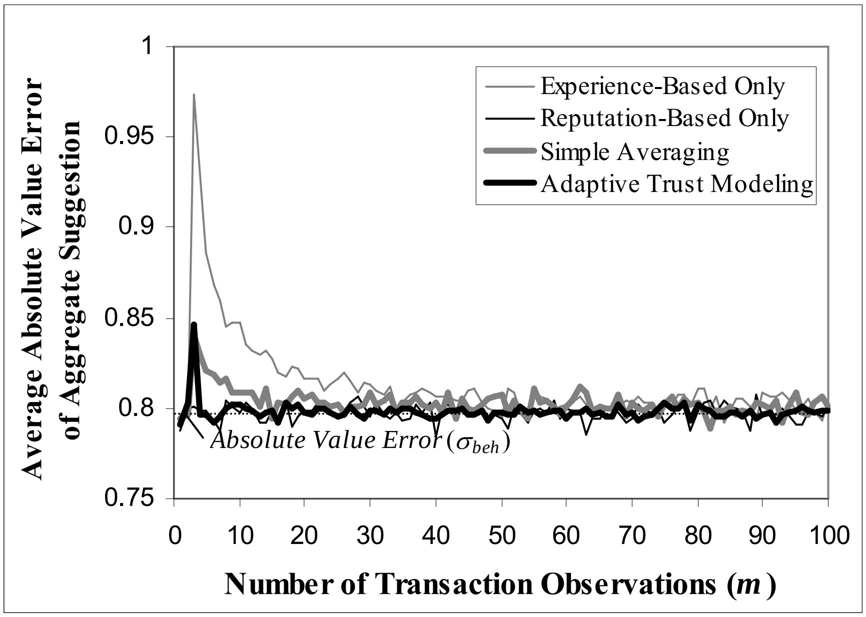


Figure 3-24. Experimental comparison of aggregate suggestion absolute value error for Experience-Based Model Only, Reputation-Based Model Only, Simple Averaging, and Adaptive Trust Modeling techniques as number of transaction observations (*m*) increases ($\sigma_{R,sug}$ = 0.0). Absolute value error for trustee behavior (σ_{beh} = 1.0), the minimum achievable error, is shown as a baseline. Solid lines are for clarity only (*m* is discrete).

When $\sigma_{R,sug}$ equals 0.3 or 0.5 (Figure 3-25 and Figure 3-26, respectively), the reputation-based model yields error lower than that of the experience-based model for low values of *m*, simply because the experience-based model's error is still decreasing (the reputation-based model is overtaken more quickly when $\sigma_{R,sug}$ equals 0.5 than when $\sigma_{R,sug}$ equals 0.3). In both cases, the error of Adaptive Trust Modeling is statistically similar (α = 0.05) to that of the reputation-based model for low values of *m*, but decreases (in correlation to the experience-based model) as *m* increases. When *m* is large, the error of Adaptive Trust Modeling is statistically similar (α = 0.05) to that of the experience-based model. When $\sigma_{R,sug}$ equals 1.0 (Figure 3-27), the reputation-based model's error is higher than that of the experience-based model immediately (when $m = 1$ and greater). As a result, the error of Adaptive Trust Modeling is statistically similar ($\alpha = 0.05$) to that of the experience-based model for all values of m.

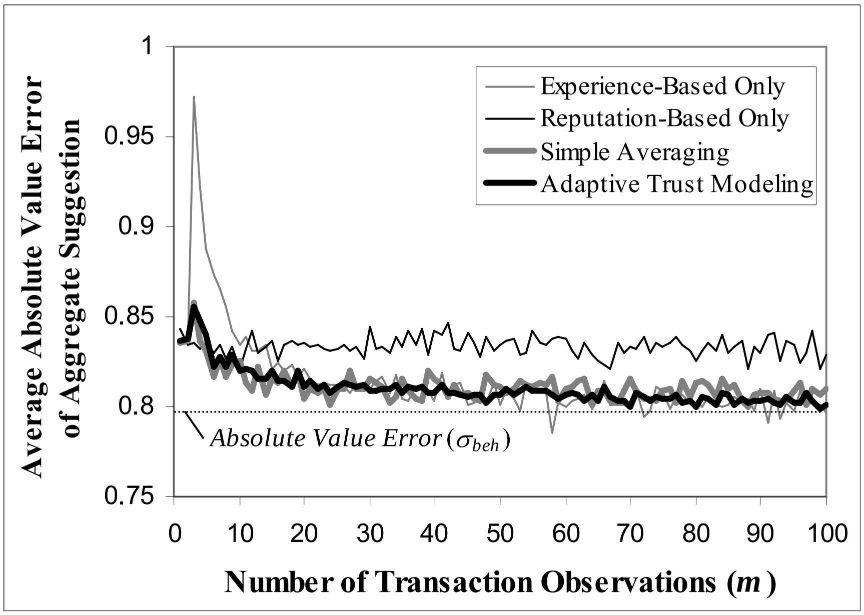


Figure 3-25. Experimental comparison of aggregate suggestion absolute value error for Experience-Based Model Only, Reputation-Based Model Only, Simple Averaging, and Adaptive Trust Modeling techniques as number of transaction observations (m) increases ($\sigma_{R,sug} = 0.3$). Absolute value error for trustee behavior ($\sigma_{beh} = 1.0$), the minimum achievable error, is shown as a baseline. Solid lines are for clarity only (m is discrete).

As further justification for the validity of Adaptive Trust Modeling, note that the error of the Adaptive Trust Modeling mechanism is as low as, or lower than, the error of all other three weighting techniques: Experience-Based Model Only, Reputation-Based Model Only, and Simple Averaging. Figure 3-28 shows $\omega_{R,\sigma_{agg,err,min}}$ as a function of m for each of the $\sigma_{R,sug}$ values explored: 0.0, 0.3, 0.5, and 1.0. In agreement with previous discussion, Adaptive Trust Modeling computes $\omega_{R,\sigma_{agg,err,min}} = 1$ over all m values when $\sigma_{R,sug}$ equals zero. For less accurate reputation-based models, (higher values of $\sigma_{R,sug}$), $\omega_{R,\sigma_{agg,err,min}}$ decreases more steeply as m increases.

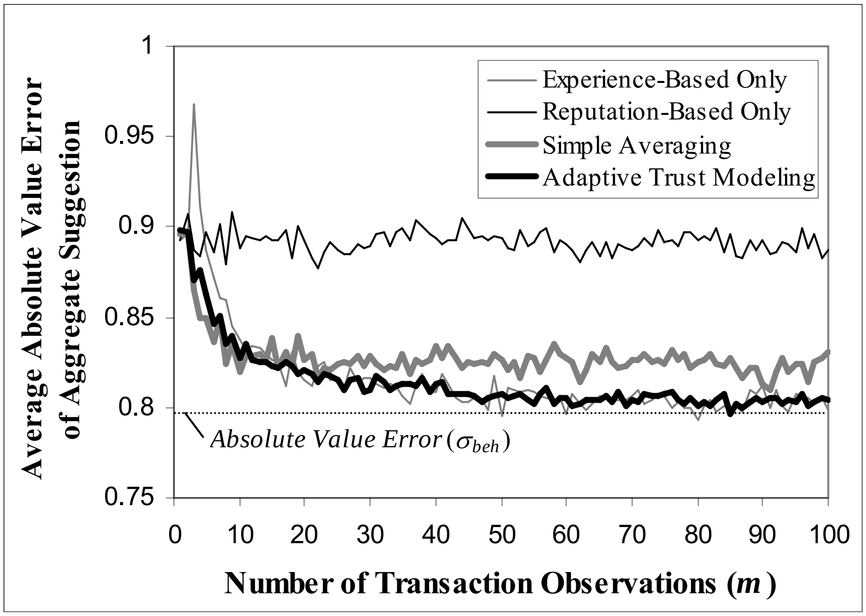


Figure 3-26. Experimental comparison of aggregate suggestion absolute value error for Experience-Based Model Only, Reputation-Based Model Only, Simple Averaging, and Adaptive Trust Modeling techniques as number of transaction observations (m) increases ($\sigma_{R,sug}$ = 0.5). Absolute value error for trustee behavior (σ_{beh} = 1.0), the minimum achievable error, is shown as a baseline. Solid lines are for clarity only (m is discrete).

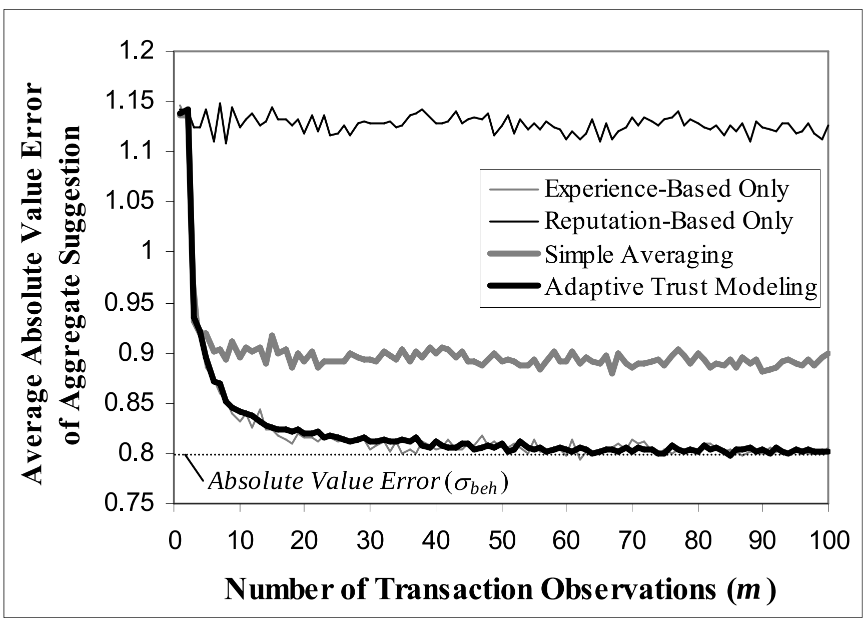


Figure 3-27. Experimental comparison of aggregate suggestion absolute value error for Experience-Based Model Only, Reputation-Based Model Only, Simple Averaging, and Adaptive Trust Modeling techniques as number of transaction observations (m) increases ($\sigma_{R,sug}$ = 1.0). Absolute value error for trustee behavior (σ_{beh} = 1.0), the minimum achievable error, is shown as a baseline. Solid lines are for clarity only (m is discrete).

In some cases, it is simplistic to assume the accuracy of an aggregate reputation-based model stays constant. In particular, a reputation-based model may become more accurate over time (assuming reputation providers are honest) as reputation providers improve their own trust models by observing transactions with the potential trustee and obtaining reputation suggestions from others.

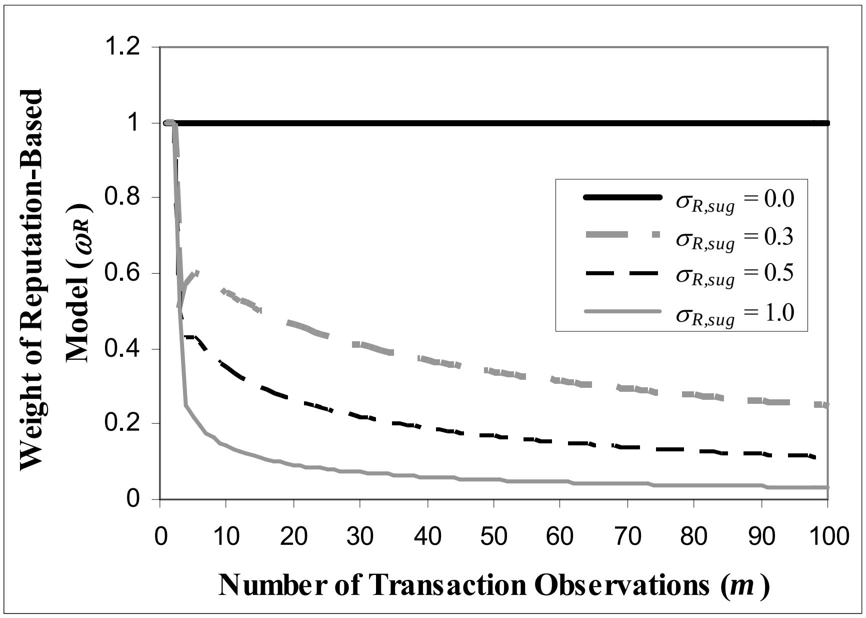


Figure 3-28. Adaptive Trust Modeling's weight (ω_R) of reputation-based model as a function of number of transaction observations (m) when $\sigma_{R,sug}$ equals 0.0, 0.3, 0.5, and 1.0. Solid lines are for clarity only (m is discrete).

To examine scenarios in which the accuracy of a reputation-based model increases over time, a reputation model building factor, b_r, is introduced, representing—as a multiple of m—the rate at which a truster's reputation-based model is built. The number, m_r, of transaction observations making up the truster's reputation-based model is computed as:

$$m_r = b_r m . \qquad \text{Eqn 31}$$

The value of b_r is greater than one in most cases, because for each of the truster's own transaction observations (making up its experience-based model), either the truster's sole reputation provider gathers multiple, independent transaction observations (through its own experience or as a "reputation broker," gathering reputations communicated by other reputation providers), or the truster receives reputations from multiple providers (who each gather at least one independent transaction observation).

The suggestion standard deviation ($\sigma_{E,sug}$) of a truster's experience-based model, as a function of *m*, is given by Equation 24 from Section 3.2.1, repeated here:

$$\sigma_{E,sug}(m) = \frac{\sigma_{beh}}{\sqrt{m}}. \qquad \text{Eqn 24}$$

The suggestion standard deviation ($\sigma_{R,sug}$) of the truster's reputation-based model is given by:

$$\sigma_{R,sug}(m) = \frac{\sigma_{beh}}{\sqrt{m_r}}$$

$$\sigma_{R,sug}(m) = \frac{\sigma_{beh}}{\sqrt{b_r m}}. \qquad \text{Eqn 32}$$

From Section 3.1.4 (Equation 13), the weight, $\omega_{R,\sigma_{agg,err,min}}$, assigned by a truster to its reputation-based model is given by:

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\sigma_{E,sug}^2}{\sigma_{E,sug}^2 + \sigma_{R,sug}^2}. \qquad \text{Eqn 13}$$

Substituting Equations 24 and 32,

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\left(\frac{\sigma_{beh}}{\sqrt{m}}\right)^2}{\left(\frac{\sigma_{beh}}{\sqrt{m}}\right)^2 + \left(\frac{\sigma_{beh}}{\sqrt{b_r m}}\right)^2}$$

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\frac{\sigma_{beh}^2}{m}}{\frac{\sigma_{beh}^2}{m} + \frac{\sigma_{beh}^2}{b_r m}}$$

$$\omega_{R,\sigma_{agg,err,min}} = \frac{\frac{b_r \sigma_{beh}^2}{b_r m}}{\frac{b_r \sigma_{beh}^2}{b_r m} + \frac{\sigma_{beh}^2}{b_r m}}$$

$$\omega_{R,\sigma_{agg,err,min}} = \frac{b_r \sigma_{beh}^2}{b_r \sigma_{beh}^2 + \sigma_{beh}^2}$$

$$\omega_{R,\sigma_{agg,err,min}} = \frac{b_r \sigma_{beh}^2}{\left(b_r + 1\right) \sigma_{beh}^2}$$

$$\omega_{R,\sigma_{agg,err,min}} = \frac{b_r}{b_r + 1} . \qquad \text{Eqn 33}$$

In the case in which experience- and reputation-based trust models improve accuracy by observing transactions, Equation 33 demonstrates that the weight, $\omega_{R,\sigma_{agg,err,min}}$, of the reputation-based model is determined by b_r alone. For example, if the reputation-based model incorporates twice as many independent transaction observations as the experience-based model in the same amount of time ($b_r = 2$), then $\omega_{R,\sigma_{agg,err,min}} = 2/3$. When $b_r = 1$, (experience- and reputation-based models increase in accuracy at the same rate), $\omega_{R,\sigma_{agg,err,min}} = 1/2$; it is intuitive that both models are weighted equally.

If the truster's reputation-based model is based on no transaction observations ($b_r = 0$), the reputation-based model has no accuracy, and $\omega_{R,\sigma_{agg,err,min}}$ appropriately equals zero. If the truster's reputation-based model is built before the truster itself observes any transactions, or, in effect, the experience-based model is never built ($b_r = \infty$), then $\omega_{R,\sigma_{agg,err,min}}$ equals one, because the truster's experience-based model is unable to contribute any accuracy. It must be remembered that both of these extreme cases assume the experience- and reputation-based models are built according to Equations 24 and 32. That is, neither model has constant accuracy (constant $\sigma_{E,sug}$ or $\sigma_{R,sug}$, respectively); both have decreasing suggestion standard deviations as dictated by m and m_r and, ultimately, the ratio b_r. Further, the assumption implies that reputation providers truthfully convey an aggregate of their own transaction observations (or independent observations truthfully conveyed to them by others). Reputation suggestions communicated by untruthful reputation providers would most likely not continue to increase in accuracy according to Equation 32. The concept of b_r, a ratio describing the relative rate at which transaction observations are acquired to build up experience- and reputation-based models, can be extended to compare rates of transaction observation acquisition between reputation providers, thus assisting the truster in selecting from individual reputation providers when building an aggregated reputation-based model (combining reputations from multiple providers is discussed in Section 3.3.2).

Table 3-2 summarizes calculations of $\sigma_{agg,err}$ for each of the weighting techniques described previously: 1) Experience-Based Model Only, 2) Reputation-Based Model Only, 3) Simple Averaging, and 4) Adaptive Trust Modeling. Figure 3-29 shows a theoretical calculation of absolute value error (as defined by Equation 28 in Section 3.2.1) when $b_r = 2$ for each of the four techniques. Error for the Experience-Based Model Only case is given by Equation 25 in Section 3.2.1:

$$\sigma_{E,err} = \sigma_{beh}\sqrt{\frac{m+1}{m}} \; . \qquad \text{Eqn 25}$$

Table 3-2. Weighting technique names, weights, and corresponding equations for aggregate error standard deviation ($\sigma_{agg,err}$).

Weighing Technique	Weights (ω_E, ω_R)	Aggregate Error Standard Deviation ($\sigma_{agg,err}$)
Experience-Based Model Only	$\omega_R = 0$ $\omega_E = 1$	$\sigma_{beh}\sqrt{\frac{(m+1)}{m}}$ (Eqn 25)
Reputation-Based Model Only	$\omega_R = 1$ $\omega_E = 0$	$\sigma_{beh}\sqrt{\frac{(b_r m+1)}{(b_r m)}}$ (Eqn 34)
Simple Averaging	$\omega_R = 0.5$ $\omega_E = 0.5$	$\sigma_{beh}\sqrt{\frac{0.25b_r + 0.25 + b_r m}{b_r m}}$ (Eqn 35)
Adaptive Trust Modeling	$\omega_R = \frac{b_r}{b_r+1}$ (Eqn 33) $\omega_E = \frac{1}{b_r+1}$	$\sqrt{\frac{1}{m\sigma_{beh}(1+b_r)} + \sigma_{beh}^2}$ (Eqn 36)

Error for the reputation-based model is calculated similarly, with $m_r = b_r m$ (Equation 31) substituting for m:

$$\sigma_{R,err} = \sigma_{beh}\sqrt{\frac{b_r m+1}{b_r m}} \; . \qquad \text{Eqn 34}$$

Error for the Simple Averaging technique is computed according to Equation 20 in Section 3.1.4:

$$\sigma_{agg,err} = \sqrt{\left(0.5\sigma_{E,sug}\right)^2 + \left(0.5\sigma_{R,sug}\right)^2 + \sigma_{beh}^2} \qquad \text{Eqn 20}$$

$$\sigma_{agg,err} = \sqrt{\left(0.5\frac{\sigma_{beh}}{\sqrt{m}}\right)^2 + \left(0.5\frac{\sigma_{beh}}{\sqrt{b_r m}}\right)^2 + \sigma_{beh}^2}$$

$$\sigma_{agg,err} = \sqrt{\frac{0.25\sigma_{beh}^2}{m} + \frac{0.25\sigma_{beh}^2}{b_r m} + \sigma_{beh}^2}$$

$$\sigma_{agg,err} = \sqrt{\frac{0.25b_r\sigma_{beh}^2 + 0.25\sigma_{beh}^2 + b_r m\sigma_{beh}^2}{b_r m}}$$

$$\sigma_{agg,err} = \sigma_{beh}\sqrt{\frac{0.25b_r + 0.25 + b_r m}{b_r m}}\,. \qquad \text{Eqn 35}$$

Finally, error for Adaptive Trust Modeling is computed from Equation 19 in Section 3.1.4:

$$\sigma_{agg,err} = \sqrt{\frac{\sigma_{E,sug}^2\sigma_{R,sug}^2}{\sigma_{E,sug}^2 + \sigma_{R,sug}^2} + \sigma_{beh}^2} \qquad \text{Eqn 19}$$

$$\sigma_{agg,err} = \sqrt{\frac{\left(\frac{\sigma_{beh}}{\sqrt{m}}\right)^2\left(\frac{\sigma_{beh}}{\sqrt{b_r m}}\right)^2}{\left(\frac{\sigma_{beh}}{\sqrt{m}}\right)^2 + \left(\frac{\sigma_{beh}}{\sqrt{b_r m}}\right)^2} + \sigma_{beh}^2}$$

$$\sigma_{agg,err} = \sqrt{\frac{\frac{\sigma_{beh}^4}{b_r m^2}}{\frac{\sigma_{beh}^2}{m} + \frac{\sigma_{beh}^2}{b_r m}} + \sigma_{beh}^2}$$

$$\sigma_{agg,err} = \sqrt{\frac{\frac{\sigma_{beh}^4}{b_r m^2}}{\frac{b_r m\sigma_{beh}^2 + m\sigma_{beh}^2}{b_r m^2}} + \sigma_{beh}^2}$$

$$\sigma_{agg,err} = \sqrt{\frac{\sigma_{beh}^4}{b_r m \sigma_{beh}^2 + m \sigma_{beh}^2} + \sigma_{beh}^2}$$

$$\sigma_{agg,err} = \sqrt{\frac{\sigma_{beh}^2}{b_r m + m} + \sigma_{beh}^2}$$

$$\sigma_{agg,err} = \sqrt{\sigma_{beh}^2 \left(\frac{1}{b_r m + m} + 1 \right)}$$

$$\sigma_{agg,err} = \sqrt{\sigma_{beh}^2 \left(\frac{1}{b_r m + m} + 1 \right)}$$

$$\sigma_{agg,err} = \sigma_{beh} \sqrt{\frac{1}{m\left(b_r + 1\right)} + 1}\,. \qquad \text{Eqn 36}$$

Figure 3-29 shows a theoretical calculation of absolute value error (computed from Equation 28 in Section 3.2.1) when $b_r = 2$ for each of the four weighing techniques. When m is small, the experience- and reputation-based models have similar levels of error. However, as m increases, the reputation-based model increases accuracy at a faster rate than the experience-based model, because the reputation-based model is based on twice as many transaction observations as the experience-based model, for any given value of m. Adaptive Trust Modeling maintains the lowest error of all techniques, computing $\omega_{R,\sigma_{agg,err,min}} = 0.67$ from Equation 33. The Simple Averaging technique maintains error almost as low as Adaptive Trust Modeling because the weights it employs ($\omega_R = 0.5$) are close to those computed by the Adaptive Trust Modeling ($\omega_{R,\sigma_{agg,err,min}} = 0.67$) in the case of $b_r = 2$.

Figure 3-30 shows empirical results from an experiment in which the four weighting techniques in Table 3-2 are compared. To simulate a reputation-based model increasing in accuracy over time, a single truster has access to an aggregated reputation-based trust model based on b_r transaction observations for every observation incorporated into the truster's experience-based model. The potential trustee behaves in such a manner that its payoff to the truster, P_{act}, follows the distribution $N(\mu_{beh} = 10, \sigma_{beh} = 1.0)$. Each run consists of 100 transaction opportunities, and results from n = 100,000 runs are averaged. Results from the experiment agree with the theoretical prediction shown in Figure 3-29. When *m* is low, Adaptive Trust Modeling achieves error (statistically, α = 0.05) signicantly lower than both Experience- and Reputation-Based Only techniques. When *m* is high, the error of Adaptive Trust Modeling is statistically similar to both Experience- and Reputation-Based Only techniques, demonstrating that the choice of weighting is less important as both experience- and reputation-based models become very accurate.

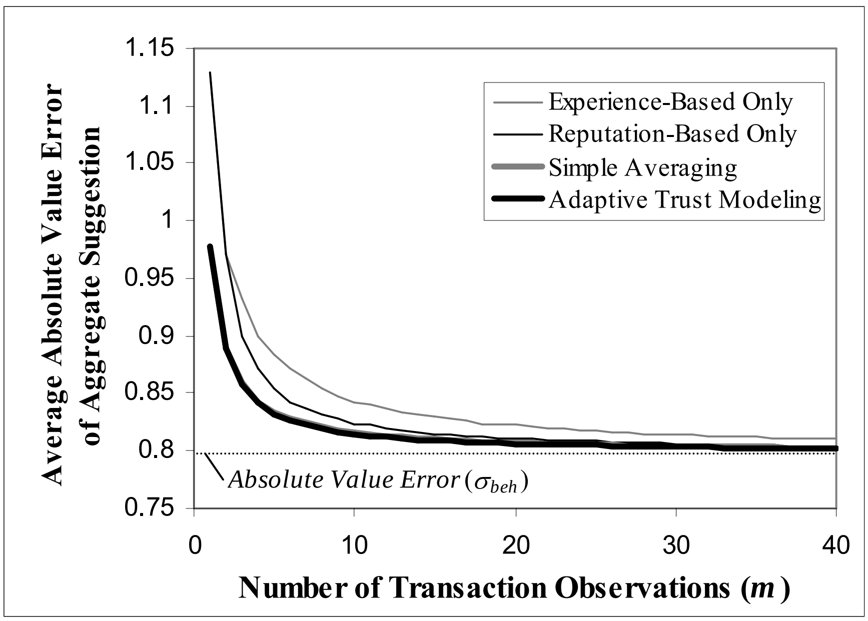


Figure 3-29. Theoretical comparison of aggregate suggestion absolute value error for Experience-Based Model Only, Reputation-Based Model Only, Simple Averaging, and Adaptive Trust Modeling techniques as number of experience-based model transaction observations (*m*) increases (b_r = 2). Absolute value error for trustee behavior (σ_{beh} = 1.0), the minimum achievable error, is shown as a baseline. For clarity, solid lines are shown (*m* is discrete).

The similarity between the predicted Adaptive Trust Modeling results and empirical results is demonstrated in Figure 3-31. Figure 3-32 shows $\omega_{R,\sigma_{agg,err,min}}$ values calculated by Adaptive Trust Modeling, as compared to theoretical $\omega_{R,\sigma_{agg,err,min}}$ values given by Equation 33 (Figure 3-32 also displays experimental and theoretical $\omega_{R,\sigma_{agg,err,min}}$ values for b_r = 1 and b_r = 10, in addition to b_r = 2). Initially, Adaptive Trust Modeling assigns $\omega_{R,\sigma_{agg,err,min}}$ as 0.5. However, as estimates of experience- and reputation-based model errors are built, $\omega_{R,\sigma_{agg,err,min}}$ converges toward 0.67, the value specified by Equation 33, when b_r = 2. It is hypothesized that experimental $\omega_{R,\sigma_{agg,err,min}}$ values require large numbers of transaction observations before reaching the theoretically-computed $\omega_{R,\sigma_{agg,err,min}}$ values because slight variations exist in experience- and reputation-based model error estimates.

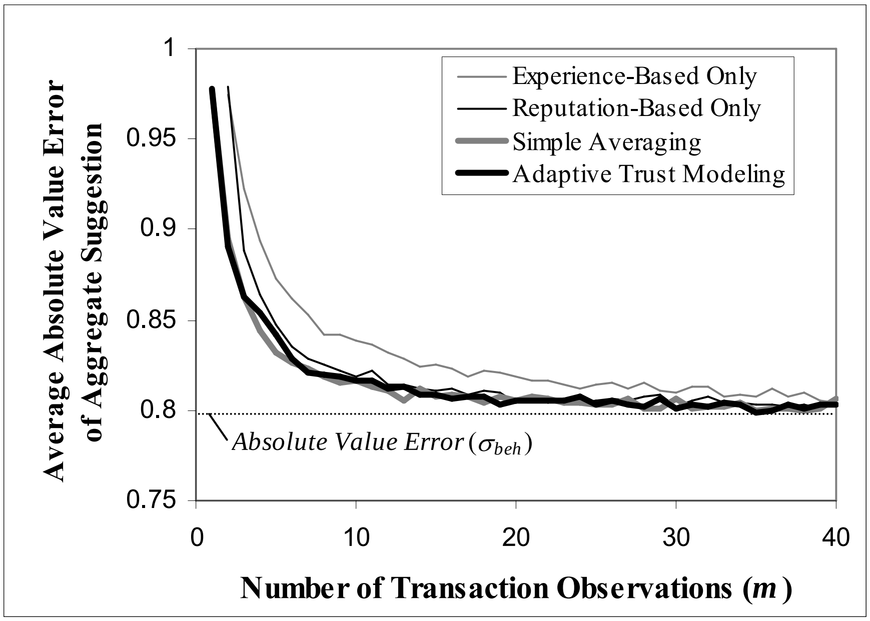


Figure 3-30. Experimental comparison of aggregate suggestion absolute value error for Experience-Based Model Only, Reputation-Based Model Only, Simple Averaging, and Adaptive Trust Modeling techniques as number of experience-based model transaction observations (*m*) increases (b_r = 2). Absolute value error for trustee behavior (σ_{beh} = 1.0), the minimum achievable error, is shown as a baseline. For clarity, solid lines are shown (*m* is discrete).

In summary, $\omega_{R,\sigma_{agg,err,min}}$, the weight of the truster's reputation-based model, as computed by Adaptive Trust Modeling, is higher when the reputation-based model's error, as indicated by its suggestion standard deviation ($\sigma_{R,sug}$) is lower. When $\sigma_{R,sug}$ is constant, the number of the experience-based model's transaction observations needed for the experience-based model to surpass the reputation-based model in accuracy depends on $\sigma_{R,sug}$. When $\sigma_{R,sug}$ is low (reputation suggestions are accurate), $\omega_{R,\sigma_{agg,err,min}}$ is slower to decrease (the truster relies on its reputation-based model longer because the experience-based model requires more transaction observations to become more accurate than the reputation-based model). Regardless of reputation-based model accuracy and number of observed transactions, Adaptive Trust Modeling dynamically identifies the optimal weighting of experience- and reputation-based models to achieve the most accurate aggregate model possible.

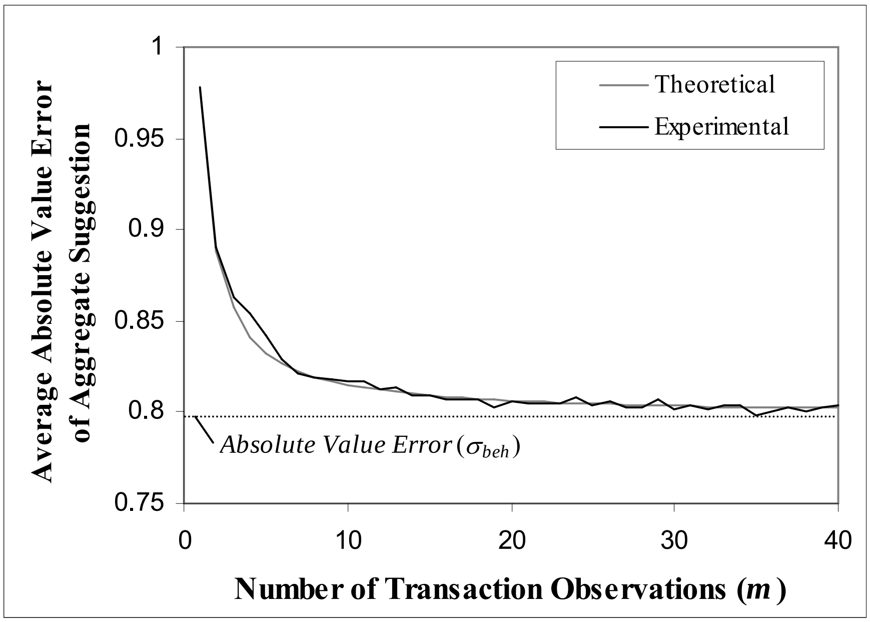


Figure 3-31. Comparison of theoretical and experimental aggregate suggestion absolute value error for Adaptive Trust Modeling as number of experience-based model transaction observations (m) increases (b_r = 2). Absolute value error for trustee behavior (σ_{beh} = 1.0), the minimum achievable error, is shown as a baseline. For clarity, solid lines are shown (m is discrete).

In some cases, the accuracy of a truster's reputation-based model increases just as its experience-based model accuracy increases, because the reputation-based model, too, is based on transaction observations. The frequency of transactions contributing to the truster's reputation-based model is usually higher than that of transactions contributing to the truster's experience-based model because the reputation-based model is made up of reputations from either several providers contributing their observations or one reputation provider contributing more frequent observations. When a truster's reputation-based model increases in accuracy for this reason (assuming reputations are truthful), higher $\omega_{R,\sigma_{agg,err,min}}$ values are computed by Adaptive Trust Modeling when the rate at which transaction observations are incorporated into the reputation-based model, relative to the rate at which transaction observations are incorporated into the truster's experience-based model, is higher.

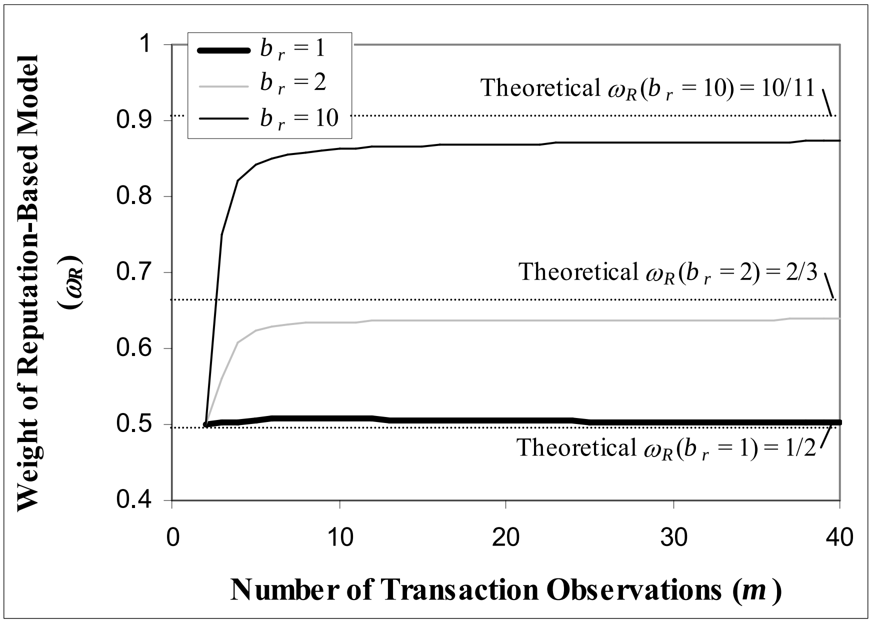


Figure 3-32. Adaptive Trust Modeling's weight (ω_R) of reputation-based model as a function of number of experience-based model transaction observations (m) (b_r = 1, 2, and 10). For comparison, theoretical weights are shown. For clarity, solid lines are shown (m is discrete).

This section helps refute Misconception 4 from Section 1.4: *A truster can rely on experience-based modeling for low-value transactions, but should always acquire reputations when considering high-value transactions.* This misconception arises from the idea that reputations are a more accurate supplement to a truster's existing experience-based model, which is not always true. In truth, a truster's decision to utilize experience vs. reputations must be based on the relative accuracy of both models. If the truster's experience-based model is more accurate than the reputations it has access to, the truster should rely more on experience than on reputations.

3.3.1.2 Performing Error-Sensitive Translation: Overcoming Mean Errors

This section serves as an aside, demonstrating the validity of Adaptive Trust Modeling's assumption that $\mu_{R,sug} = \mu_{beh}$ for a reputation-based trust model's suggestions and, therefore, $\mu_{R,err} = 0$. Error-Sensitive Translation is introduced, by which a reputation model's suggestions are adjusted to eliminate consistent errors of suggestion mean, $\mu_{R,err}$

(Equation 21 in Section 3.2.1 demonstrates that error mean for experience-based models, $\mu_{E,err}$, is theoretically always zero). Intuitively, reputation suggestions that are highly consistent (low suggestion distribution standard deviation, $\mu_{R,sug}$) provide valuable information, regardless of their suggestions' error distribution mean. For instance, if a celebrity has a clothing advisor who always recommends the wrong outfit for every occasion (such as a tuxedo for an afternoon barbecue event), the celebrity might wear the opposite of what the advisor recommends (casual attire instead of the tuxedo), thereby performing a reflective transformation on the recommendation. As another example, a malfunctioning mass scale might always report values that are five kilograms greater than the true mass being weighed; in this case the human scale reader might perform a translative transformation on the reported mass, subtracting five kilograms to arrive at the correct mass reading. Similarly, a MySpace user seeking friends might discount reputations about strangers if the user knows that all recommenders are overly positive. In each example, the provided suggestions are useful, despite inaccuracies, because the consistency of the provider gives the suggestion receiver a transformation by which to correct the suggestion's inaccuracy.

Throughout the discussion of weighting two (Section 3.1.4) or more (later in Section 3.3.2) suggestions to derive an aggregate suggestion, it has been assumed that trust models from which those suggestions derive have error means (μ_{err}) of zero. However, a reputation provider i may have an error distribution with a mean other than zero, providing reputation suggestions that are overly pessimistic ($\mu_{R_i,err}$ < 0) or overly optimistic ($\mu_{R_i,err}$ > 0). Averaging of reputation suggestions without accounting for differences in error means produces aggregate suggestions with distorted values. Nevertheless, usefulness is gleaned from reputation providers with consistent (low $\sigma_{R_i,err}$) yet inaccurate (high $\left|\mu_{R_i,err}\right|$) reputation suggestions. Error-Sensitive Translation performs a translation for nonzero error means to produce an adjusted suggestion, $P'_{R_i,sug}$:

$$P'_{R_i,sug} = P_{R_i,sug} - \mu_{R_i,err}$$

Note that, theoretically, experience-based trust models always have error means equal to zero, based on Equation 21 in Section 3.2.1. Since

$$\mu_{E,sug}(m) = \mu_{beh},$$

therefore,

$$\mu_{E,err}(m) = \mu_{E,sug}(m) - \mu_{beh} = 0.$$

An experiment is conducted to assess the validity of performing Error-Sensitive Translation when reputation provider error means ($\mu_{R_i,err}$) are nonzero. In the experiment, a single truster has access to only an aggregated reputation-based trust model which produces suggestions from the distribution $N(\mu_{R,sug}, \sigma_{R,sug})$, where $\mu_{R,sug} = \mu_{beh} + \mu_{R,err}$ and $\sigma_{R,sug} = 1.0$. Adaptive Trust Modeling is not implemented, since the truster's experience-based model is ignored. Suggestion error mean, $\mu_{R,err}$, takes on values of 0.0, 0.5, 1.0, and 2.0. The potential trustee behaves in such a manner that its payoff to the truster, P_{act}, follows the distribution $N(\mu_{beh} = 10, \sigma_{beh} = 1.0)$. Each run consists of 100 transaction opportunities, and results from n = 10,000 runs are averaged.

Two translation approaches are compared against an approach of No Translation: 1) Always Translation and 2) Error-Sensitive Translation. The Always Translation approach performs translation even early on, when m is very low, even though the truster's estimate of $\mu_{R,err}$ is very primitive. Error-Sensitive Translation generates two hypothetical suggestions for each reputation-based suggestion: one that has undergone translation and one that has not. Error-Sensitive Translation continues to utilize the non-translated hypothetical suggestion in its aggregate suggestion computation until the error of a given translated hypothetical suggestion is lower than the error of its corresponding non-translated hypothetical suggestion; at this point, the trustee begins using the translated hypothetical suggestion instead.

Figure 3-33 compares average absolute value error (as defined by Equation 28 in Section 3.2.1), for No Translation, Always Translation, and Error-Sensitive Translation approaches, when $\mu_{R,err} = 2.0$, as a function of number of transaction observations m. For reference, the theoretical minimum error achievable (when $\mu_{R,err} = 0.0$) is shown as a baseline, where

$$theoretical\ minimum\ error = \sigma_{R,err}\sqrt{\frac{2}{\pi}}$$

$$theoretical\ minimum\ error = \sqrt{\left(\sigma_{R,sug}^2 + \sigma_{beh}^2\right)\frac{2}{\pi}}.$$

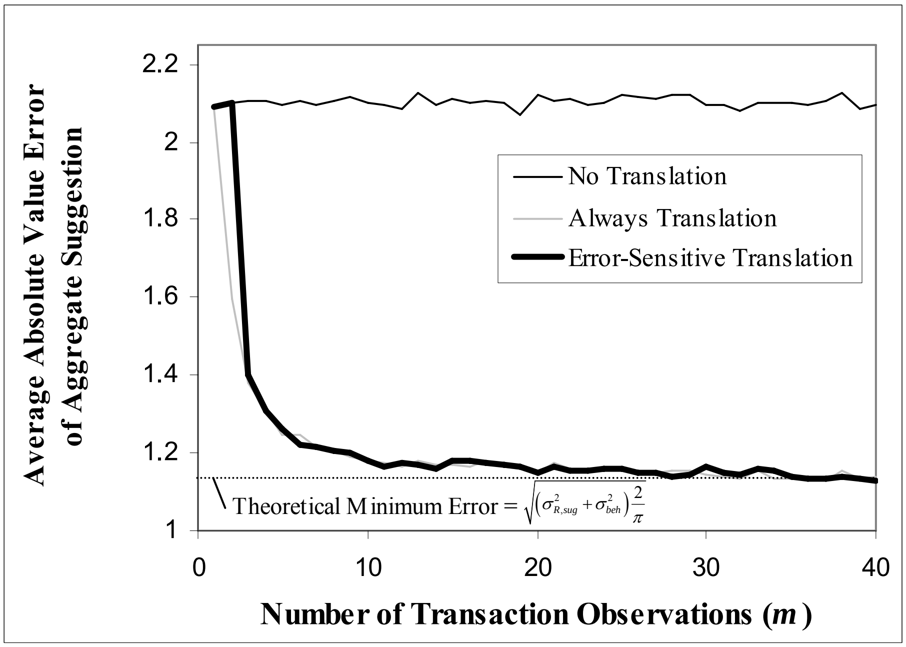


Figure 3-33. Aggregate suggestion absolute value error for Reputation-Based Model Only weighting technique as number of transaction observations (*m*) increases ($\mu_{R,err}$ = 2.0). The following translation techniques are compared: 1) No Translation, 2) Always Translation, and 3) Error-Sensitive Translation. The theoretical minimum achievable error (for σ_{beh} = 1.0 and $\sigma_{R,sug}$ = 1.0), is shown as a baseline. For clarity, solid lines are shown (*m* is discrete).

Although the average absolute value errors of Always Translation and Error Sensitive Translation approaches are initially (when $m = 1$) statistically ($\alpha = 0.05$) similar to that of the No Translation approach, errors of both translation approaches decline significantly over the first few transactions as additional observations provide more certainty about the appropriate translation magnitude (reputation providers' error, $\mu_{R,err}$). As m increases, the error of the Always Translation and Error-Sensitive Transaction approaches are statistically similar and significantly lower than No Translation. The Always Translation approach begins its decline one transaction observation before the Error Sensitive Translation approach; the Error Sensitive Translation approach waits for an indication that error due to translation will decrease average absolute value error before beginning translation. Nevertheless, the Error Sensitive Translation approach begins translation almost immediately, since $|\mu_{R,err}|$ is large compared to $\sigma_{R,err}$.

In Figure 3-34, average absolute value error is compared among the three translation approaches for $\mu_{R,err}$ = 1.0. In this case, the Always Translation approach performs translation with too few transaction observations (and, thus, an inaccurate estimate of $\mu_{R,err}$), resulting in higher average absolute value error than the No Translation approach when m < 3. The Error Sensitive Translation approach avoids this error spike by waiting until m = 3 to begin performing translation. As m increases, the error of the Always Translation and Error-Sensitive Transaction approaches are statistically similar and significantly lower than No Translation.

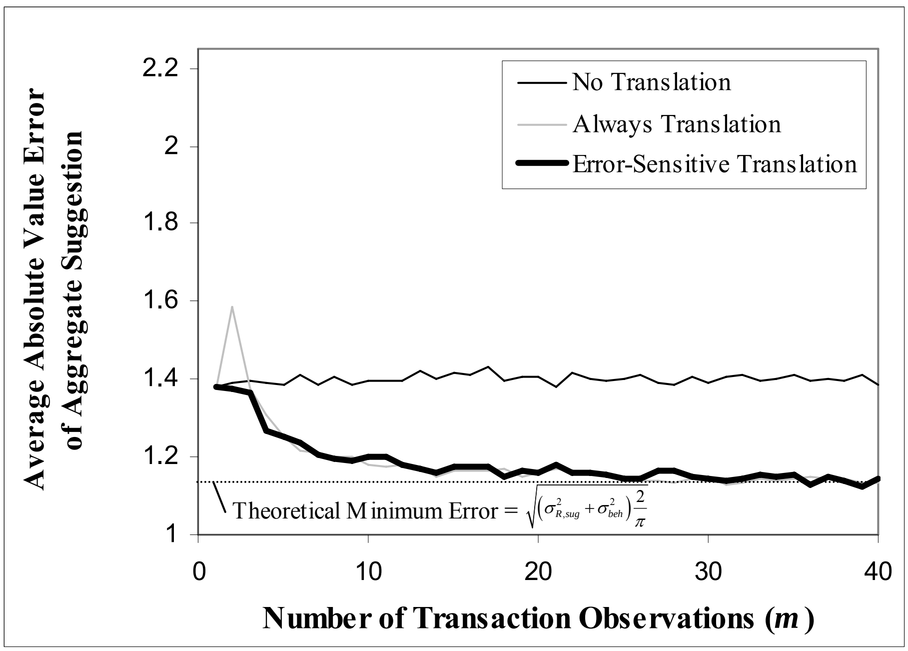


Figure 3-34. Aggregate suggestion absolute value error for Reputation-Based Model Only weighting technique as number of transaction observations (m) increases ($\mu_{R,err}$ = 1.0). The following translation techniques are compared: 1) No Translation, 2) Always Translation, and 3) Error-Sensitive Translation. The theoretical minimum achievable error (for σ_{beh} = 1.0 and $\sigma_{R,sug}$ = 1.0), is shown as a baseline. For clarity, solid lines are shown (m is discrete).

Figure 3-35 compares average absolute value error among the three translation approaches for $\mu_{R,err}$ = 0.5. Again, the Always Translation approach performs translation with too few transaction observations (and, thus, an inaccurate estimate of $\mu_{R,err}$), resulting in higher average absolute value error than the No Translation approach when $m < 6$. The Error Sensitive Translation's slight error spike when $m < 6$ is due to imprecision in error estimates for two hypothetical (translated and non-translated) suggestions when $|\mu_{R,err}|$ is small compared to $\sigma_{R,err}$. As m increases, the error of the Always Translation and Error-Sensitive Transaction approaches are statistically similar and significantly lower than No Translation.

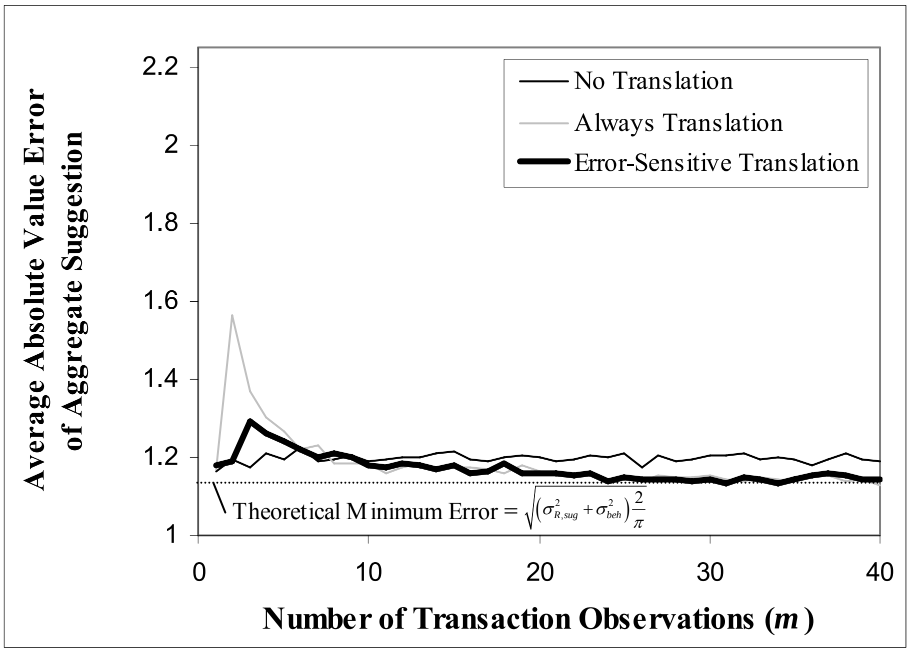


Figure 3-35. Aggregate suggestion absolute value error for Reputation-Based Model Only weighting technique as number of transaction observations (m) increases ($\mu_{R,err}$ = 0.5). The following translation techniques are compared: 1) No Translation, 2) Always Translation, and 3) Error-Sensitive Translation. The theoretical minimum achievable error (for σ_{beh} = 1.0 and $\sigma_{R,sug}$ = 1.0), is shown as a baseline. For clarity, solid lines are shown (m is discrete).

Similarly, Figure 3-36 compares average absolute value error among the three translation approaches for $\mu_{R,err} = 0.0$. Error Sensitive Translation decreases the error spike due to translation (as opposed to Always Translation) when m is small; however, an error spike still exists since $\mu_{R,err}$ is infinitely small ($\mu_{R,err} = 0$) compared to $\sigma_{R,sug}$. For all values of $\mu_{R,err}$, error of the Error Sensitive Translation approach converges to the theoretical minimum error as m increases. As m increases, the error of all approaches are statistically similar. Because of slight error spikes early on (when m is small) in Figure

3-35 and Figure 3-36, a system designer might choose to disable Error-Sensitive Translation if it is known that $|\mu_{R,err}|$ is significantly less than $\sigma_{R,err}$. Figure 3-37 shows average absolute value error (asymptote values approximated at m = 100) as a function of $\mu_{R,err}$, demonstrating that translation achieves largest decreases in average absolute value error when $|\mu_{R,err}|$ is large compared to $\sigma_{R,sug}$.

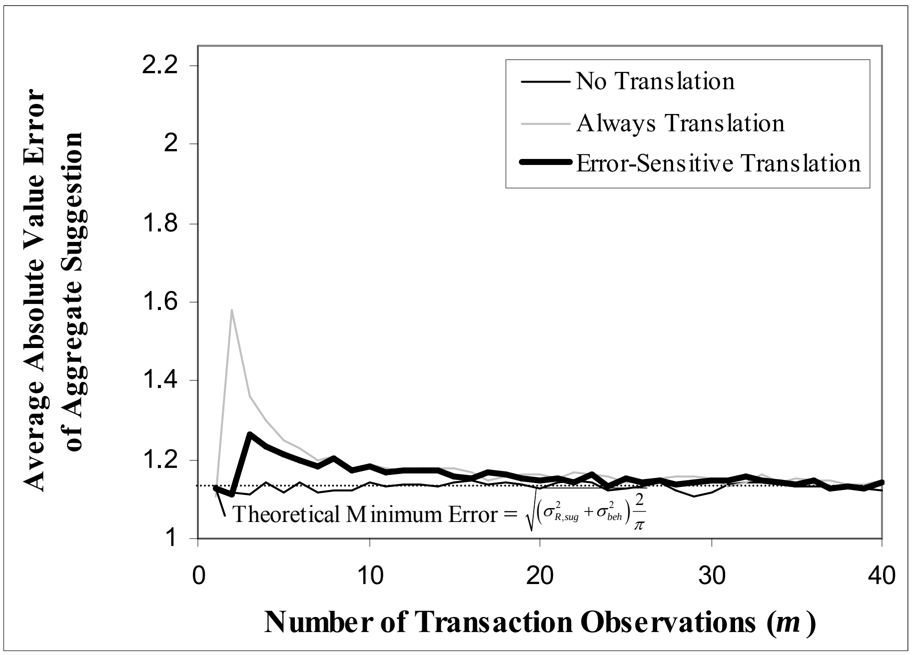


Figure 3-36. Aggregate suggestion absolute value error for Reputation-Based Model Only weighting technique as number of transaction observations (m) increases ($\mu_{R,err}$ = 0.0). The following translation techniques are compared: 1) No Translation, 2) Always Translation, and 3) Error-Sensitive Translation. The theoretical minimum achievable error (for σ_{beh} = 1.0 and $\sigma_{R,sug}$ = 1.0), is shown as a baseline. For clarity, solid lines are shown (m is discrete).

In summary, transformations (in particular, Error-Sensitive Translation, as demonstrated here) enable a truster to utilize consistent, if inaccurate, suggestions from reputation providers. By tracking the previous accuracy ($\mu_{R,err}$) of reputation providers, the truster alters the reputation suggestions it receives to improve suggestion accuracy. Error-Sensitive Translation is most effective when $|\mu_{R,err}|$ (the magnitude of the provider's inaccuracy) is large compared to $\sigma_{R,err}$ (related to the provider's consistency), though Error-Sensitive Translation succeeds in minimizing error due to unnecessary translations when $|\mu_{R,err}|$ is less than $\sigma_{R,err}$.

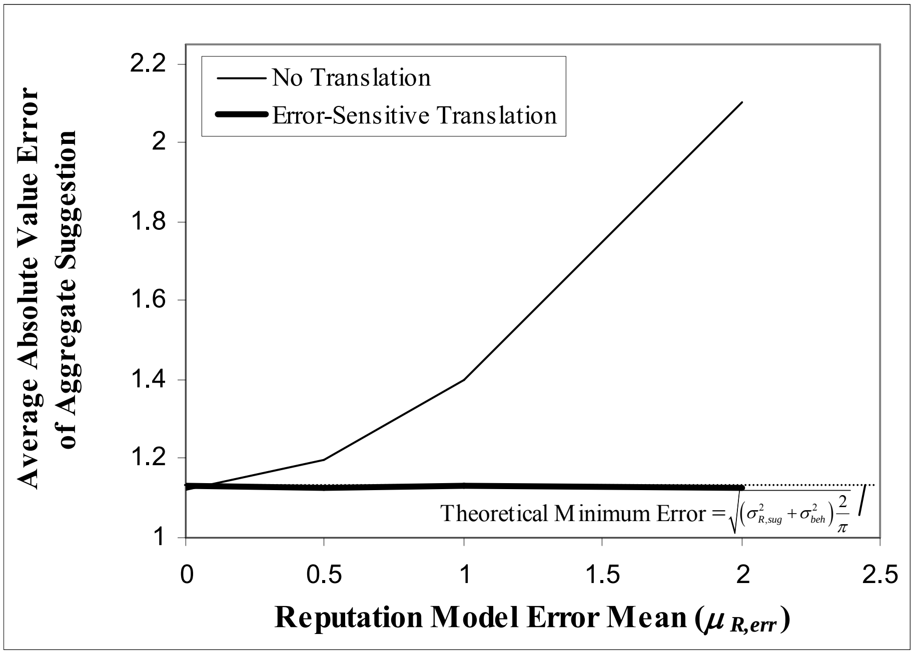


Figure 3-37. Aggregate suggestion absolute value error for Reputation-Based Model Only weighting technique as number of transaction observations ($\mu_{R,err}$) increases (asymptotic values estimated at *m* ~ 100). No Translation and Error-Sensitive Translation techniques are compared (Always Translation yields values similar to Error-Sensitive Translation). The theoretical minimum achievable error (for σ_{beh} = 1.0 and $\sigma_{R,sug}$ = 1.0), is shown as a baseline.

This section refutes Misconception 3 from Section 1.4: *Inaccurate reputation providers are never useful.* In truth, if a reputation provider produces reputations that, though inaccurate, have consistent error, the truster can perform Error-Sensitive Translation on those reputations, according to error magnitude, to achieve useful information about a trustee.

3.3.2 REPUTATION COST

Reputations often have an acquisition cost in terms of communication, time, or purchase price. When reputation costs are high, a truster is likely to purchase fewer reputations, resulting in a reputation-based trust model that is less accurate than when reputations costs are low. As a result, the truster is more willing to rely on trust information it already has (i.e. the truster's experience-based model). For example, when selecting a restaurant, a diner is more likely to casually ask friends in the same room about restaurant reputations than to locate and telephone a local food critic. Even though the food critic's reputations may be more valuable (assuming the critic is more knowledgeable than the diner's friends and evaluates restaurants based on similar preferences), the communication and time cost to ask friends, "What do you think of Restaurant X?" is significantly lower than locating and acquiring reputations from a stranger. The diner is even less likely to drive to a bookstore and buy a local restaurant guide; in this case, acquiring reputations would require significant amounts of both time and money.

The value of the transaction influences a truster's willingness to pay for reputations, as well. If the transaction value is high, a truster is willing to invest more in acquiring reputations because each reputation yields a greater increase in transaction payoff that if the overall transaction value is low. Continuing the restaurant example, if the diner is planning an anniversary dinner for his wife, he may be more likely to purchase the restaurant guide than if he is simply trying to find a quick lunch between errands. Evaluating exactly how much reputation information to acquire, in light of reputation cost, is a difficult problem which requires a truster to weigh reputation acquisition cost against the estimated increase in transaction payoff due to a reputation's contribution to increased aggregate trust model accuracy. Chapter 4, which introduces Adaptive Cost Selection, is dedicated to this problem of 1) assessing the value of trust information—specifically reputations—in terms of resulting increase in transaction payoff and 2) determining the appropriate trust information to acquire, in light of the information's acquisition cost. In particular, Section 4.1.5 discusses the impact of transaction magnitude (risk) on a truster's willingness to spend resources to acquire trust information, as illustrated by the restaurant example.

Previous discussion in this chapter has represented suggestions from reputation-based models simply as aggregated values whose error is described by $\sigma_{R,err}$. In reality, however, the truster may have numerous reputation providers—each providing reputations of varying accuracy—from which to choose in building its aggregated reputation-based model. Because this section discusses acquisition of individual reputations based on cost, it is important to understand how individual reputations are combined to form an aggregated reputation-based model. As an extension of Equation 15 in Section 3.1.4, reputations are weighted according to the inverse variance of suggestions from their providers.

$$\omega_{R_i,\sigma_{agg,err,min}} = \frac{\frac{1}{\sigma^2_{R_i,sug}}}{\sum_j \frac{1}{\sigma^2_{R_j,sug}}}. \qquad \text{Eqn 15}$$

This research assumes the selection of individual reputation providers is determined before the reputations they provide are known to the truster. Additional techniques for computing weights to minimize aggregate error, based on the values of the provided reputations, may be available, such as outlier exclusion [Fullam and Barber, 2004]. This assumption is in effect because the truster often must commit to using (or, at least, acquiring) reputations before viewing them when reputations are obtained for a price.

Recall from Equation 5 in Section 3.1.4 that a provider's $\sigma_{R_i,sug}$ is indicative of its error, $\sigma_{R_i,err}$ ($\sigma_{R_i,err}$ is influenced by σ_{beh}, which describes variation in trustee behavior, and $\sigma_{R_i,sug}$). Past suggestions used to estimate a provider's $\sigma_{R_i,sug}$ value need not necessarily concern the specific trustee in question. The truster may include suggestions received from the provider about other trustees, if the truster deems the group of trustees to all be of similar "type." For example, if a reputation provider has delivered several suggestions about trustees with regard to their abilities as lawyers, the truster might use those suggestions to compute the provider's $\sigma_{R_i,sug}$ for weighting suggestions about a new lawyer as a potential trustee. However, the truster might not utilize those same suggestions when gauging the reputation provider's ability to deliver suggestions about an auto mechanic.

Figure 3-38 illustrates how weights for several reputation suggestions may be determined by Equation 15 (momentarily ignoring the truster's experience-based model). As an extension of Equation 17 in Section 3.1.4, the truster's resulting minimum expected suggestion standard deviation ($\sigma_{R,agg,sug,min}$) for all aggregated reputations is given by,

$$\sigma_{R,agg,sug,min} = \sqrt{\frac{1}{\sum_j \frac{1}{\sigma^2_{R_j,sug}}}}, \qquad \text{Eqn 37}$$

and minimum expected error standard deviation is given by

$$\sigma_{R,agg,err,min} = \sqrt{\frac{1}{\sum_j \frac{1}{\sigma^2_{R_j,sug}}} + \sigma^2_{beh}}. \qquad \text{Eqn 38}$$

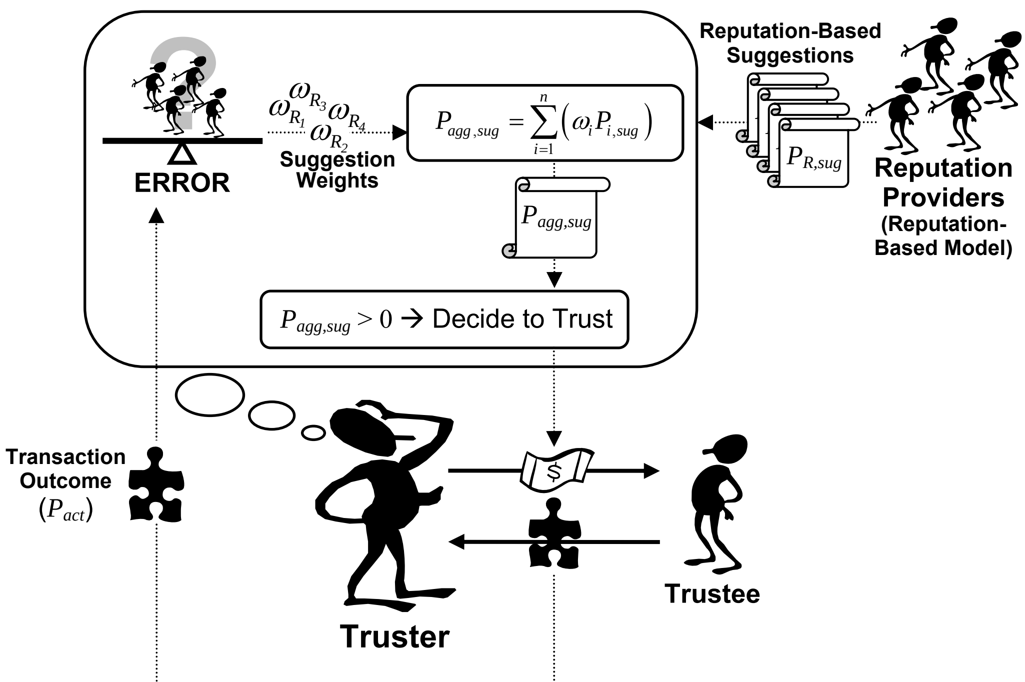


Figure 3-38: The Adaptive Trust Modeling technique illustrating weighting of several reputation suggestions (the experience-based model is excluded from this figure). The truster decides whether to trust a potential trustee by performing a weighted average of suggestions from multiple reputation providers. Weights are determined by relative error of each reputation provider. The transaction outcome is used to update the truster's error estimates for each reputation provider.

Figure 3-39 shows aggregate error standard deviation for an aggregate suggestion (composed of three reputation suggestions) for varying combinations of ω_1, ω_2, and ω_3. In the experience-included case (Figure 3-40), the truster's experience-based model is viewed as an additional "reputation provider" whose suggestions have zero cost and error that decreases as the number of transaction observations (with the trustee in question) increases.

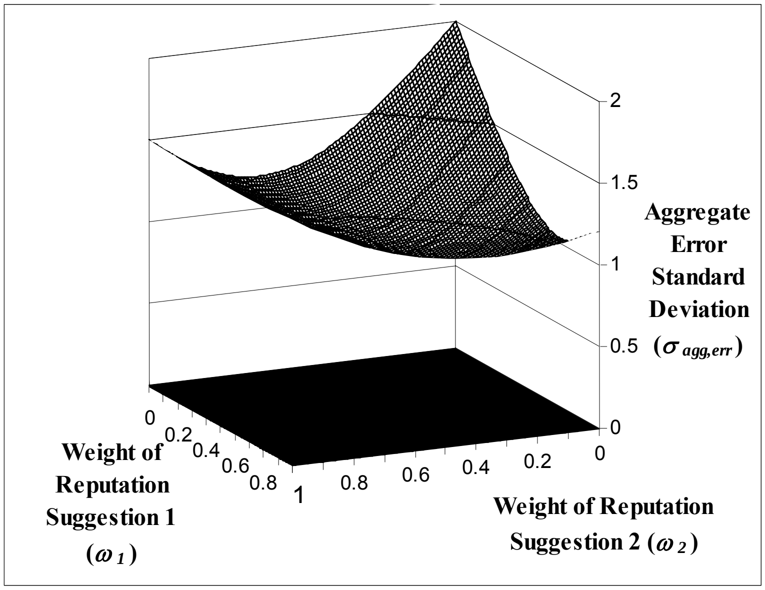


Figure 3-39. Aggregate error standard deviation ($\sigma_{agg,err}$) as a function of two out of three reputation suggestion weights (ω_1 and ω_2). The value of $\sigma_{agg,err}$ is minimized when ω_1 and ω_2 (and, thus, ω_3) are computed according to Equation 15.

The objective of Chapter 3 is to answer Research Question 1 by determining how environment factors, including reputation cost, influence a truster's reliance on its experience vs. reputation-based models. Adaptive Cost Selection (an algorithm in Chapter 4 for selecting reputations based on reputation provider accuracy and reputation cost) has not yet been introduced. However, in the interest of Chapter 3 continuity, this section shows experimental results demonstrating the impact of reputation cost on a truster's Adaptive Trust Modeling weights for experience- vs. reputation-based trust models. In this experiment, the truster employs Adaptive Cost Selection, which is assumed to be an appropriate technique for assessing the tradeoff between reputation accuracy (contribution to increasing transaction payoff) and cost. The experiment is further detailed in Section 4.2.1, where Adaptive Cost Selection is validated.

This experiment compares the weight ($\omega_{R,\sigma_{agg,err,min}}$) of a truster's reputation-based model (an aggregation of acquired reputations) for different values of reputation cost

$Cost(R_i)$. The single truster has access to its experience-based model, as well as ten reputation providers, each providing reputation suggestions according to $N(\mu_{R_i,sug}$, $\sigma_{R_i,sug})$, where $\mu_{R_i,sug} = \mu_{beh}$ and $\sigma_{R_i,sug} = 10.0$. An experiment run consists of 100 transaction observations (m), during which the truster builds its experience-based trust model about a single trustee whose behavior (P_{act}) is normally distributed according to $N(\mu_{beh}, \sigma_{beh})$, where $\sigma_{beh} = 1.0$. The trustee's μ_{beh} is constant throughout a run, but over different runs, each with a different trustee, μ_{beh} is uniformly distributed between $P_{act,min} = -10.0$ and $P_{act,max} = 10.0$. Results from 9000 runs are averaged.

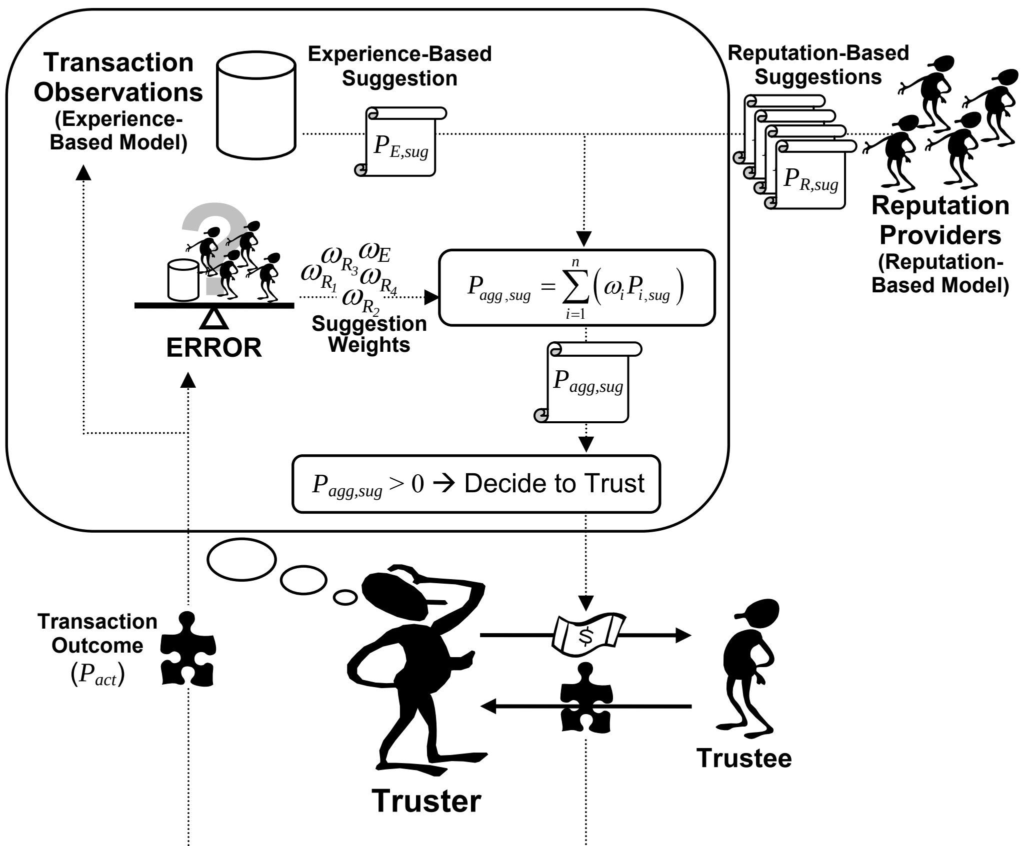


Figure 3-40: The Adaptive Trust Modeling mechanism illustrating weighting of several reputation suggestions, as well as experience-based suggestions. The truster decides whether to trust a potential trustee by performing a weighted average of suggestions from its experience-based model and multiple reputation-based trust models.

Figure 3-41 shows $\omega_{R,\sigma_{agg,err,min}}$ as a function of number of transaction observations (m) when $Cost(R_i)$ equals 0.0, 0.02, 0.1, and 0.2. As confirmed earlier in Section 3.2.1 and Section 3.3.1.1, the truster's reliance ($\omega_{R,\sigma_{agg,err,min}}$) on its reputation-based model decreases as the truster obtains more transaction observations (and accuracy of its experience-based model increases) for all values of $Cost(R_i)$. However, when $Cost(R_i)$ is high, $\omega_{R,\sigma_{agg,err,min}}$ drops more quickly (with fewer transaction observations) than when $Cost(R_i)$ is low. Figure 3-42 shows the average number of reputations purchased as a function of number of transaction observations; the truster is unwilling to acquire as many reputations when $Cost(R_i)$ is higher. When reputation cost is zero, the truster acquires nearly all ten available reputations; in contrast, when reputation cost is 0.2, the truster acquires no more than one reputation. The number of reputations acquired decreases as m increases and the accuracy of the truster's experience-based model begins to outweigh the accuracy of the truster's aggregated reputation-based model.

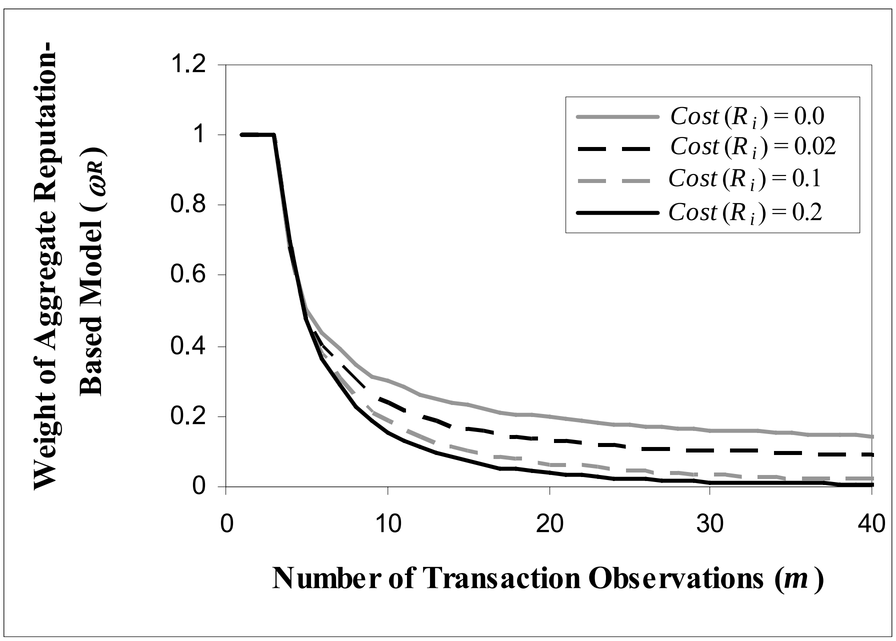


Figure 3-41. Weight of truster's aggregate reputation-based model vs. number of transaction observations for several values of reputation cost ($Cost(R_i)$).

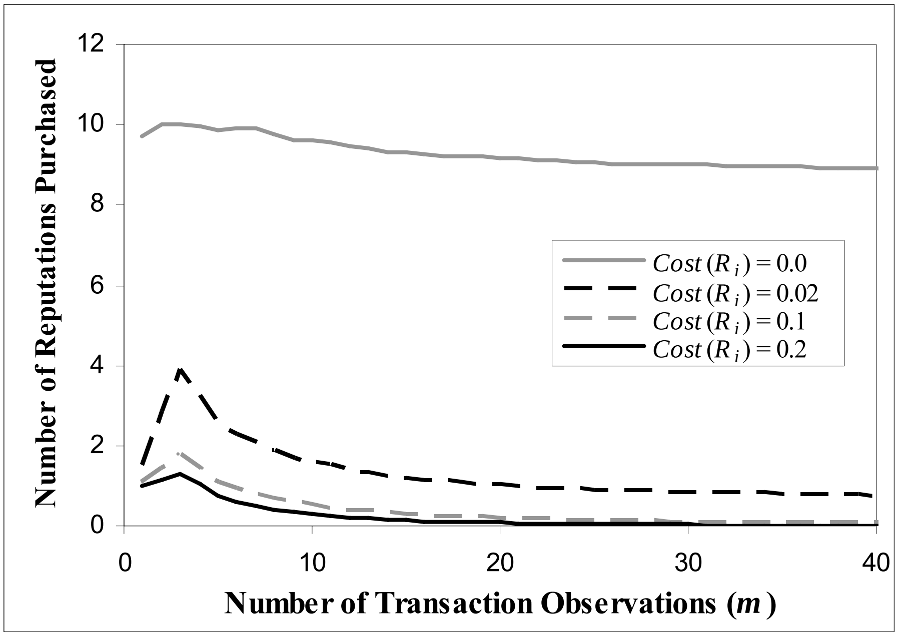


Figure 3-42. Number of reputations purchased vs. number of transaction observations for several values of reputation cost (*Cost*(*R*$_i$)).

In summary, high reputation cost limits a truster's ability to build an accurate reputation-based trust model, since a truster is unable to purchase as many reputations. A truster's decision about how much to invest in purchasing reputations is influenced by the magnitude of the transaction in question and the accuracy of the truster's alternative free (experience-based) trust model. As the truster's number of transaction observations increases, the truster purchases fewer reputations, since the accuracy of the truster's experience-based model begins to outweigh the accuracy of its reputation-based model, given the number of reputations it can afford to purchase. Chapter 4 explains Adaptive Cost Selection, by which a truster assesses the value of trust information, in terms of resulting increase in transaction payoff, and determines the appropriate trust information to acquire, in light of the information's acquisition cost.

This section helps refute Misconception 4 from Section 1.4: *A truster can rely on experience-based modeling for low-value transactions, but should always acquire reputations when considering high-value transactions.* In truth, a truster's decision to utilize experience vs. reputations must consider the cost of reputations relative to transaction value, as well as the relative accuracy of both models. If reputation costs are too expensive (relative to transaction value, even though transaction value is high), the truster may choose to rely on experience, or, if no experience-based model exists, on no model at all. Further, this section refutes Misconception 5 from Section 1.4: *A truster should always acquire only the single or few "best" reputations.* In truth, when reputations are free to acquire, a truster achieves the lowest predicted error by aggregating as many reputations as possible, weighting each according to estimated error.

Chapter 4

ADAPTIVE COST SELECTION: VALUATING TRUST INFORMATION

This chapter answers Research Question 2: *How should a truster assess the value of trust information (specifically, reputations), in light of the cost of that information, to determine what trust information to acquire?* The following objective is accomplished: presentation of the Adaptive Cost Selection algorithm for assessing the value of trust information (in particular, reputation suggestions), which enables a truster to determine what reputations to acquire in consideration of reputation cost. Section 4.1 explains Adaptive Cost Selection; by knowing the worth of a given piece of trust information (suggestion), a truster can decide how much time, effort, and money it is willing to invest to acquire that suggestion. Section 4.2 validates the Adaptive Cost Selection algorithm through experimentation, exhibiting how Adaptive Cost Selection identifies the optimal tradeoff between aggregate trust model accuracy and cost of acquired trust information to maximize the truster's payoff from transactions with trustees. Section 4.3 applies Adaptive Cost Selection to the ART Testbed domain problem, demonstrating that Adaptive Cost Selection, over existing ART Testbed strategies, improves truster decisions regarding suggestion acquisition when cost is a factor.

4.1 Adaptive Cost Selection Algorithm

In many real-world situations, a truster can only acquire suggestions (in particular, reputations) through purchasing. At a minimum, the truster usually recognizes some cost (in terms of time or effort) to acquire reputations. Evaluating the benefit of purchasing reputations requires comparison of two seemingly disparate quantities: accuracy (of the aggregate suggestion influenced by the reputation suggestions) and cost (to purchase the reputation suggestions). However, upon closer examination, a link is observed: aggregate suggestion error directly influences transaction payoff. Therefore, if error among purchased reputations, and thus aggregate suggestion error, can be correlated to transaction payoff, then a truster can select the best combination of reputation suggestions to purchase for greatest aggregate suggestion accuracy, in light of reputation cost. From Section 3.3.2, if reputation cost is high, the truster will purchase fewer reputations and must ensure that the reputations purchased are the most accurate available. The algorithm presented in this section, called Adaptive Cost Selection, enables a truster to determine how many and which reputations to purchase when there is a cost associated with acquiring reputations. Throughout this section, it is assumed that the content (the communicated estimate $P_{R_i,sug}$) of a reputation suggestion is not known to the truster until after it has been purchased to avoid the truster's reliance on techniques such as outlier detection [Fullam and Barber, 2004] for determining suggestion weights.

While acquiring reputations has obvious costs—cost of time and communication, in addition to prices charged by reputation providers—the cost to acquire experience-based suggestions (by building an experience-based model to generate those suggestions) is hidden as possible losses to untrustworthy trustees and time spent conducting transactions. A truster can consider these experience costs as investments in building its experience-based trust model that last beyond the single transaction. Although this chapter focuses on evaluating reputation costs, assessing the value of experience-based trust information can help a truster determine the amount of effort it should put forth to build its experience-based trust model.

4.1.1 Determining Probability of Trusting

Adaptive Cost Selection, and the cost analysis of reputation purchasing, begins with a study of payoff received by the truster as a function of both truster decision (to trust vs. not trust) and trustee behavior (about how trustworthy to be, in terms of transaction payoff to the truster). Referring to the payoff matrix in Figure 3-2 of Section 3.1.1, when the truster chooses to trust, it receives the payoff intended by the trustee (P_{act}), here called P_T. P_{act} may take on any of a range of values, negative or positive depending on whether—and the degree to which—the trustee chooses to fulfill its agreement; the magnitude of P_{act} is determined by the magnitude of trustworthy or untrustworthy behavior the trustee wishes to conduct. If the truster chooses not to trust, it receives a payoff, $P_{\neg T}$, of zero; since no transaction takes place, the truster does not receive the payoff P_{act} intended by the trustee (note that the value of P_{act}, the payoff intended by the trustee, itself may be influenced by the truster's decision to trust or not trust). To summarize,

$$P_T\left(P_{act}\right) = P_{act} \text{ and}$$
$$P_{\neg T}\left(P_{act}\right) = 0\,.$$

The truster's decision whether to trust is described in terms of a binary probability distribution, where $Prob(T)$ and $Prob(\neg T)$ represent the probabilities the truster will choose to trust or not trust, respectively (note that $Prob(T) + Prob(\neg T) = 1$). $Prob(T|P_{act})$ represents the probability the truster chooses to trust given the hypothetical transaction results in the trustee's decision to provide a net payoff to the truster of P_{act} (of course, the truster does not know P_{act} a priori). The truster's average payoff, *Reward*, over all transaction opportunities for a given trustee decision P_{act}, is calculated as

$$Reward\left(P_{act}\right) = Prob\left(T \mid P_{act}\right) P_T\left(P_{act}\right) + Prob\left(\neg T \mid P_{act}\right) P_{\neg T}\left(P_{act}\right)$$
$$Reward\left(P_{act}\right) = Prob\left(T \mid P_{act}\right)\left(P_{act}\right) + Prob\left(\neg T \mid P_{act}\right)\left(0\right)$$
$$Reward\left(P_{act}\right) = Prob\left(T \mid P_{act}\right) P_{act} \qquad \text{Eqn 39}$$

The truster's probabilities of trusting ($Prob(T|P_{act})$) and not trusting ($Prob(\neg T|P_{act})$) are dependent upon suggestions made by the trust models it has at its disposal. Further, the appropriateness of $Prob(T|P_{act})$ and $Prob(\neg T|P_{act})$ (that is, the truster's likelihood of choosing to trust when $P_{act} > 0$ and choosing to not trust when $P_{act} \leq 0$) depends on the accuracy of those suggestions. In this section (Section 4.1), the truster is assumed to have a several potential reputation providers from whom it may purchase reputation suggestions, here simply called "reputations" (the truster's experience-based model is ignored until Section 4.2.1). In the best case, the reputations purchased by the truster result in an aggregate suggestion $P_{agg,sug}$ with a highly-accurate prediction of transaction outcome, such that

$$P_{agg,sug} = P_{act}$$

and, therefore,

$$Prob\left(T \mid P_{act} > 0\right) = 1 \text{ and}$$

$$Prob\left(T \mid P_{act} \le 0\right) = 0 .$$

That is, in the best case, the truster should choose to trust only when the transaction results in a positive payoff. As a result, in the best case,

$$Reward\left(P_{act}\right) = P_{act} \text{ when } P_{act} > 0 \text{, and}$$
$$Reward\left(P_{act}\right) = 0 \text{ when } P_{act} \le 0.$$

Figure 4-1 shows *Prob*(T) (Figure 4-1a), *Prob*($\neg T$) (Figure 4-1b), and *Reward* (Figure 4-1c) as functions of P_{act}, within the range $P_{act,min}$ to $P_{act,max}$, for this best case scenario.

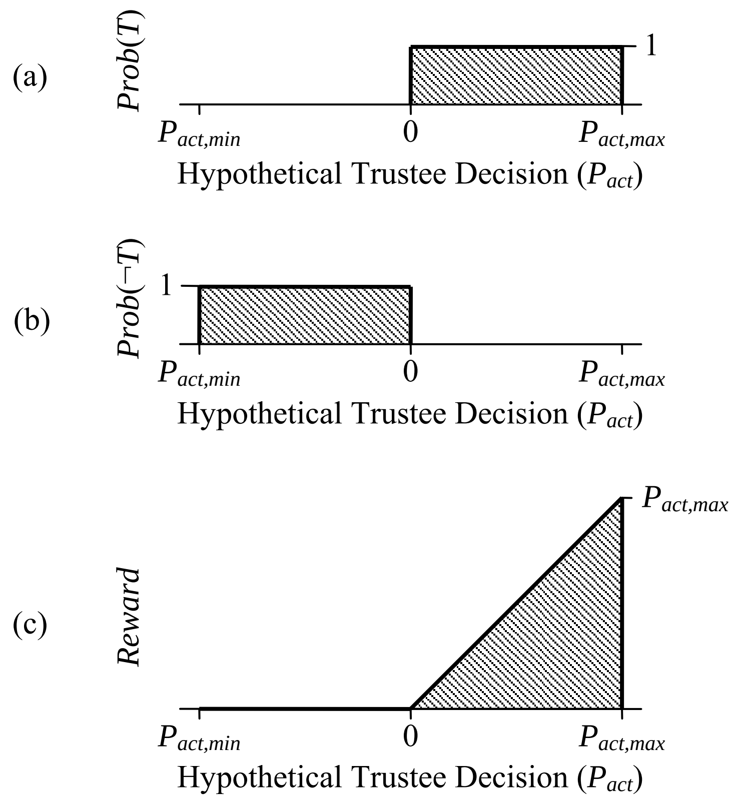


Figure 4-1. In the truster's best-case scenario (truster's aggregate suggestion exactly predicts transaction outcome), (a) probability of the truster choosing to trust (*Prob*(*T*)), (b) probability of the truster choosing to not trust *Prob*(¬*T*), and (c) truster's average payoff (*Reward*) as functions of the trustee's decision (P_{act}) about the hypothetical transaction's net payoff to the truster.

Alternatively, when purchased reputations result in an aggregate suggestion $P_{agg,sug}$ with random prediction of transaction outcome (no correlation between $P_{agg,sug}$ and P_{act}),

$$Prob\left(T \mid P_{act}\right) = 0.5 \text{ for all } P_{act}.$$

As a result,

$$Reward\left(P_{act}\right) = 0.5P_{act} \text{ for all } P_{act}.$$

Figure 4-2 shows *Prob*(*T*) (Figure 4-2a), *Prob*(¬*T*) (Figure 4-2b), and *Reward* (Figure 4-2c) as functions of P_{act}, within the range $P_{act,min}$ to $P_{act,max}$, for this random scenario.

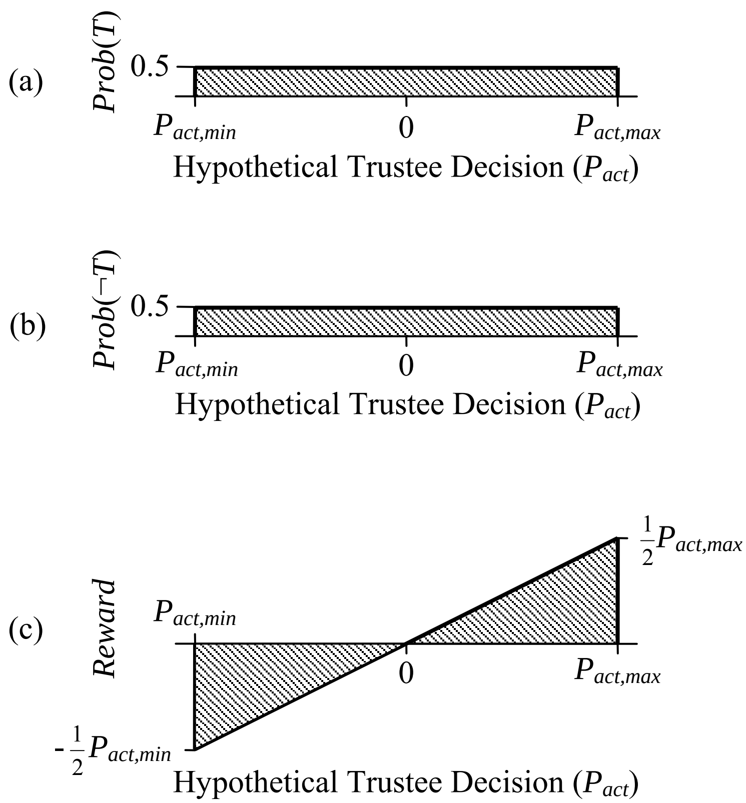


Figure 4-2. In the truster's random-case scenario (truster's aggregate suggestion is random), (a) probability of the truster choosing to trust (*Prob*(*T*)), (b) probability of the truster choosing to not trust *Prob*(¬*T*), and (c) truster's average payoff (*Reward*) as functions of the trustee's decision (P_{act}) about the hypothetical transaction's net payoff to the truster.

In the worst case, when purchased reputations yield an aggregate suggestion $P_{agg,sug}$ that predicts the opposite of the actual transaction outcome ($P_{agg,sug}$ = - P_{act}),

$$Prob\left(T \mid P_{act} > 0\right) = 0 \text{ and}$$
$$Prob\left(T \mid P_{act} \leq 0\right) = 1.$$

As a result,

$$Reward\left(P_{act}\right) = 0 \text{ when } P_{act} > 0, \text{ and}$$
$$Reward\left(P_{act}\right) = P_{act} \text{ when } P_{act} \leq 0.$$

Figure 4-3 shows *Prob*(*T*) (Figure 4-3a), *Prob*(¬*T*) (Figure 4-3b), and *Reward* (Figure 4-3c) as functions of P_{act}, within the range $P_{act,min}$ to $P_{act,max}$, for this worst case scenario.

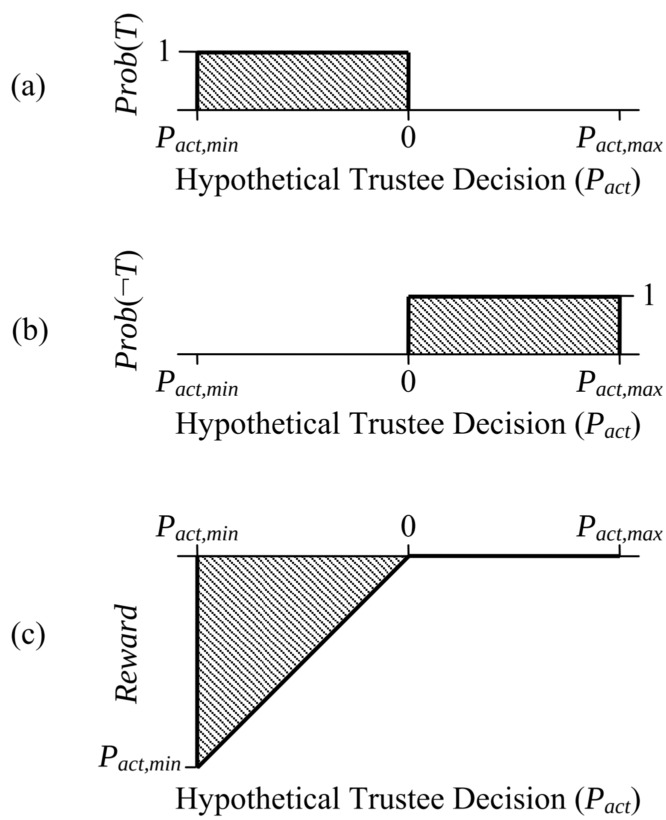


Figure 4-3. In the truster's worst-case scenario (truster's aggregate suggestion predicts the opposite of transaction outcome), (a) probability of the truster choosing to trust (*Prob*(*T*)), (b) probability of the truster choosing to not trust *Prob*(¬*T*), and (c) truster's average payoff (*Reward*) as functions of the trustee's decision (P_{act}) about the hypothetical transaction's net payoff to the truster.

The relationship between *Prob*(*T*) and the accuracy of the aggregate suggestion $P_{agg,sug}$ can be generalized to describe cases in which the aggregate suggestion has intermediate levels of accuracy. The truster will choose to trust if the net payoff it expects to receive for the given transaction ($P_{agg,sug}$) is greater than zero (a net profit, as opposed to a net loss). Therefore, the probability that the truster will choose to trust is equal to the probability that the aggregate suggestion (expected payoff $P_{agg,sug}$) is greater than zero, or, the integral, from zero to infinity, of the probability density function (*PDF*) describing the aggregate suggestion:

$$Prob\left(T \mid P_{act}\right) = \int_0^{\infty} \left(PDF\left(P_{agg,sug}, z\right)\right) dz \,. \qquad \text{Eqn 40}$$

This section will assume an example case, in which the aggregate suggestion $P_{agg,sug}$ has an error distribution $N(0, \sigma_{agg,err})$. Thus, the aggregate suggestion itself follows the distribution $N(P_{act}, \sigma_{agg,err})$, where $\sigma_{agg,err}$ is indicative of the aggregate suggestion's accuracy in predicting P_{act} ($\sigma_{agg,err} = 0$ corresponds to the best case in Figure 4-1, while $\sigma_{agg,err} = \infty$ corresponds to the random case in Figure 4-2). The probability density function of the suggestion's normal distribution is given by

$$PDF\left(P_{agg,sug}, P_{act}\right) = \frac{e^{-\frac{\left(P_{act} - P_{agg,sug}\right)^2}{2\sigma_{agg,err}^2}}}{\sigma_{agg,err}\sqrt{2\pi}} \,,$$

therefore,

$$Prob\left(T \mid P_{act}\right) = \int_0^{\infty} \left(\frac{e^{-\frac{\left(z - P_{agg,sug}\right)^2}{2\sigma_{agg,err}^2}}}{\sigma_{agg,err}\sqrt{2\pi}} \right) dz \,.$$

Figure 4-4 shows the probability density function of an aggregate suggestion distributed normally as $N(P_{act}, \sigma_{agg,err})$. The shaded portion of the figure represents *Prob*(*T*), the probability that the truster chooses to trust. The likelihood of $P_{agg,sug}$ correctly predicting $P_{act} > 0$ (indicating the truster should choose to trust) is improved by lower $\sigma_{agg,err}$ (aggregate suggestion error) relative to $|P_{act}|$ (distance from the $P_{act} = 0$ decision point).

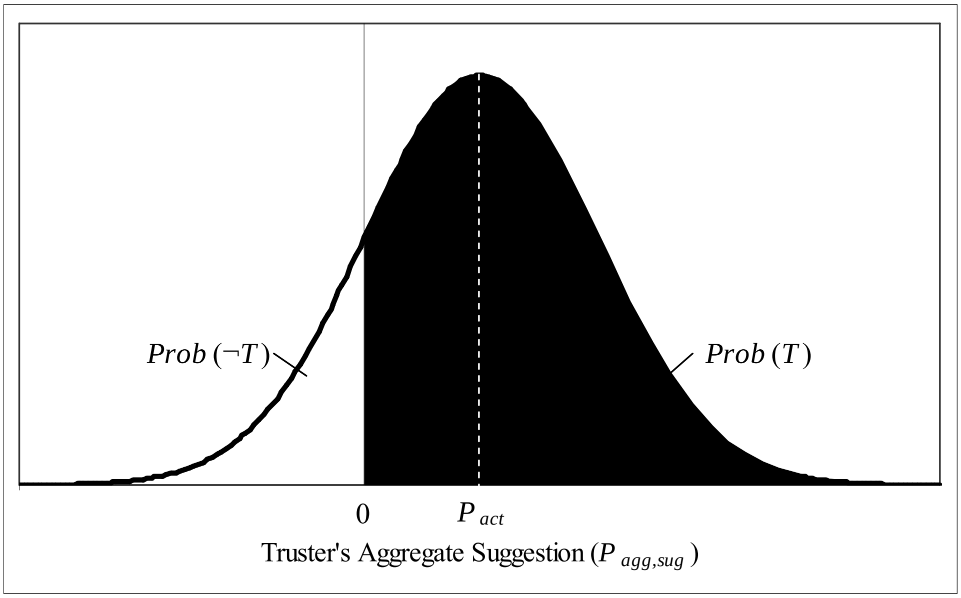


Figure 4-4. Probability density function of a truster's aggregate suggestion ($P_{agg,sug}$) with distribution $N(P_{act}, \sigma_{agg,err})$. The probability that the truster chooses to trust ($Prob(T)$) is shown by the shaded portion of the figure; the probability that the truster chooses to not trust ($Prob(\neg T)$) is shown by the unshaded portion.

Figure 4-5 charts $Prob(T)$ as a function of P_{act} for aggregate suggestions with varying accuracy (different error standard deviations $\sigma_{agg,err}$), where $P_{act,min}$ = -10 and $P_{act,max}$ = 10. When the aggregate suggestion is exact (error distribution is $N(0,0)$), the corresponding $Prob(T)$ function in Figure 4-5 matches Figure 4-1a; there is zero probability the truster will trust when trustee decision results in cheating ($P_{act} \leq 0$) and complete probability of trusting when trustee decision results in not cheating ($P_{act} > 0$). When the aggregate suggestion is random (error distribution is $N(0,\infty)$), the corresponding $Prob(T)$ function in Figure 4-5 matches Figure 4-2a; there is 50% probability the truster will trust, whether trustee decisions result in cheating or not cheating (all P_{act}), assuming $P_{act,min} = P_{act,max}$. In Figure 4-5, the corresponding $Prob(T)$ function's deviation from the correct decision (not trust when $P_{act} \leq 0$ or trust when $P_{act} >$ 0) is larger for larger values of $\sigma_{agg,err}$. The deviations occur most in the region nearest P_{act} = 0, when there is most uncertainty about whether trustee behavior P_{act} will be positive vs. negative. Figure 4-5 does not address the case described by Figure 4-3, in which purchased reputations yield an aggregate suggestion that predicts the opposite of the actual transaction outcome P_{act}. However, it is possible for the truster to perform a transformation (more specifically, a reflection) on the suggestion; the suggestion would then fit the scenarios described by Figure 4-5 (transformations, in particular, Error-Sensitive Translations, are described in Section 3.3.1.2).

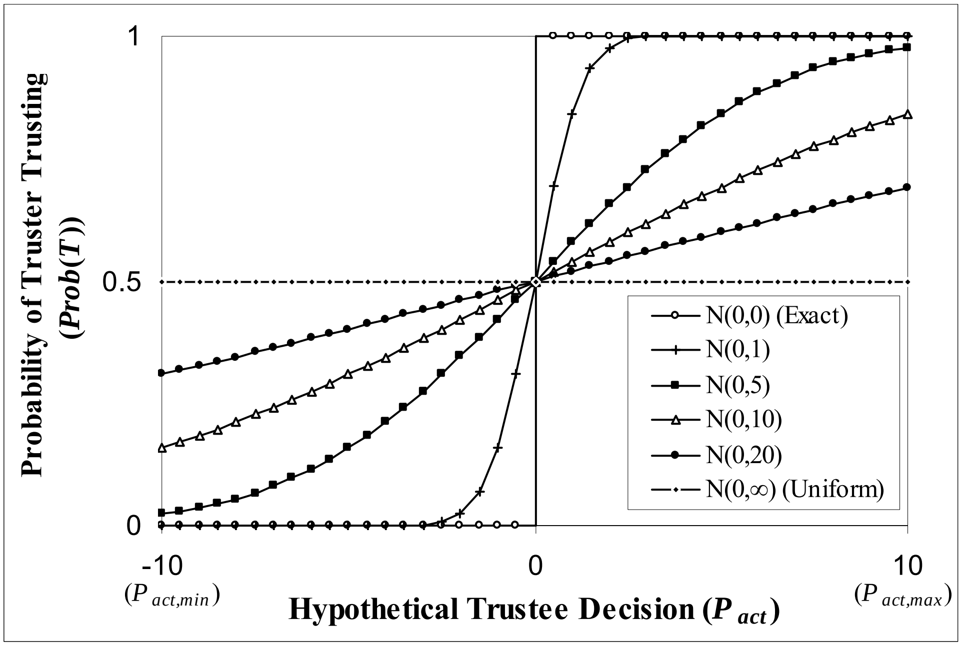


Figure 4-5. Probability that truster chooses to trust ($Prob(T)$), as a function of the trustee's decision about the hypothetical transaction's net payoff to the truster (P_{act}) for several distributions of $P_{agg,sug}$ ($\sigma_{agg,err}$ = 0, 1, 5, 10, 20, and ∞). $P_{act,min}$ = -10 and $P_{act,max}$ = 10.

4.1.2 CALCULATING *AVERAGEREWARD*

Extending Equation 39, the average payoff, *Reward*, resulting from a given trustee decision P_{act} is equal to the probability of the truster choosing to trust multiplied by the payoff received from trusting, P_{act}:

$$Reward\left(P_{act}\right) = Prob\left(T \mid P_{act}\right) P_{act} . \qquad \text{Eqn 39}$$

Substituting Equation 40:

$$Reward\left(P_{act}\right) = P_{act} \int_0^{\infty} \left(\frac{e^{-\frac{\left(z-P_{agg,sug}\right)^2}{2\sigma^2}}}{\sigma\sqrt{2\pi}} \right) dz . \qquad \text{Eqn 41}$$

Figure 4-6 charts average payoff, *Reward*, as a function of P_{act} for aggregate suggestions with varying accuracy (different error standard deviations $\sigma_{agg,err}$). When the aggregate suggestion is exact (error distribution is $N(0,0)$), the corresponding function $Reward(P_{act})$ in Figure 4-6 matches Figure 4-1c. The truster receives: 1) the maximum possible average payoff (*Reward*) P_{act} (the amount given by the trustee) when the trustee is trustworthy ($P_{act} > 0$), because a transaction does occur, and 2) zero when the trustee is untrustworthy ($P_{act} \leq 0$), because no transaction occurs. When the aggregate suggestion is random (error distribution is $N(0,\infty)$), the corresponding function $Reward(P_{act})$ in Figure 4-6 matches Figure 4-2c. The truster receives a low average payoff (*Reward*); in fact, when $P_{act,min} = P_{act,max}$, average payoff earned for transactions in which $P_{act} > 0$ is canceled out by the negative average payoff for transactions in which $P_{act} < 0$, since $Reward(P_{act}) = 0.5P_{act}$ for both positive and negative P_{act}. Average payoff (*Reward*) for $\sigma_{agg,err} > 0$ cases is lower that in the $\sigma_{agg,err} = 0$ case, especially when trustee decisions are close to $P_{act} = 0$, where there is more uncertainty about whether trustee decisions P_{act} will be positive vs. negative. When trustee decisions P_{act} are very far from zero, the $\sigma_{agg,err} > 0$ cases behave similarly to the $\sigma_{agg,err} = 0$ case; relatively slight suggestion errors are inconsequential when suggestions $P_{agg,sug}$, and trustee decisions P_{act}, are far from zero (relative to $\sigma_{agg,err}$).

By summing *Reward* values for a given $\sigma_{agg,err}$ over all possible trustee decisions according to trustee decision probabilities, $\sigma_{agg,err}$ of the aggregate suggestion can be linked to expected average payoff (over numerous transactions with full spectrum of trustee behavior). Trustee decisions are assumed to follow a uniform distribution with limits $P_{act,max}$ and $P_{act,min}$. Therefore the probability distribution function $PDF_{P_{act}}\left(P_{act}\right)$ describing the distributions of trustee decisions P_{act} is given by

$$PDF_{P_{act}}\left(P_{act}\right)=\begin{cases} \dfrac{1}{P_{act,max}-P_{act,min}} & ,P_{act,min} \leq P_{act} \leq P_{act,max} \\ 0 & ,P_{act} < P_{act,min} \text{ and } P_{act} > P_{act,max} \end{cases}$$

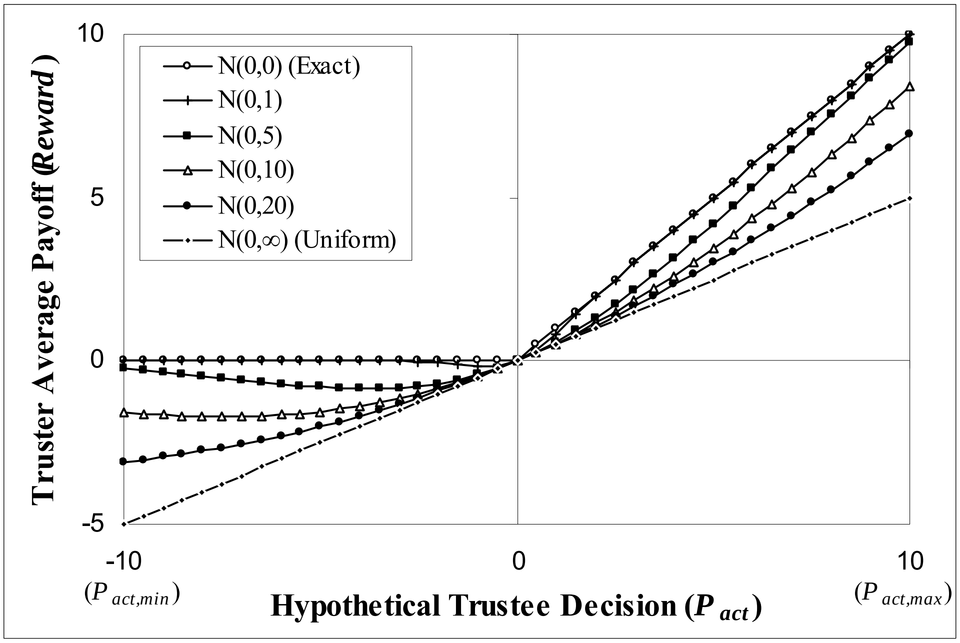


Figure 4-6. Truster average payoff (*Reward*), as a function of the trustee's decision (P_{act}) about the hypothetical transaction's net payoff to the truster, for several distributions of $P_{agg,sug}$ ($\sigma_{agg,err}$ = 0, 1, 5, 10, 20, and ∞). $P_{act,min}$ = -10 and $P_{act,max}$ = 10.

The distribution of trustee decisions (P_{act}) can be assumed uniform via the following explanation. The context of this payoff analysis is reputation-based trust modeling (deciding which reputations to purchase). As demonstrated in Section 3.1.1, reputation-based trust modeling is useful during initial transactions with a single trustee, since the number of observed transactions (m) is too low for an experience-based model to be accurate yet. Second, reputation-based modeling is employed when a trustee changes its decision pattern frequently and in unpredictable ways (described in Section 3.2.3), since the truster can never observe enough transactions to build up an accurate experience-based model before the trustee's decision pattern changes. Third, reputation-based modeling is used in scenarios consisting of one-time transactions with several trustees, since no transactions with a given trustee are observed prior to the transaction in question (m = 0). In each of these three scenarios described, since a trustee's previous decisions either are no indication of future decisions (in the case of a trustee with changing decision patterns) or have never been observed, the truster may view the trustee for each potential transaction as an unknown. From the truster's perspective, the trustee's decision may result in any value P_{act} within known limits P_{max} and P_{min}; therefore, assuming truster decisions to be uniformly distributed is reasonable.

Nonetheless, situations may exist in which a different distribution of trustee decisions might be assumed. An environment may be known, in general, to consist of mostly cheaters (for example, when trustees are dishonest used car salesmen) or mostly altruistic trustees (for example, when trustees are benevolent churches). In these cases, the overall trustee decision distribution might be skewed negative or positive, respectively. However, if the truster knows enough about trustee characteristics to skew the trustee decision distribution, then reputations are most likely not very useful anyway; accurate reputations are most valuable when there is a large amount of uncertainty as to whether trustee decisions tend toward cheating ($P_{act} < 0$) or not ($P_{act} > 0$), as described above and shown in Figure 4-6. Section X relaxes the assumption that P_{max} and P_{min} are known to the truster a priori.

Given $Reward(P_{act})$ (the average payoff expected for a given trustee decision P_{act}) for a given aggregate suggestion error standard deviation, $\sigma_{agg,err}$, and $PDF_{P_{act}}\left(P_{act}\right)$ (the estimated distribution of trustee decisions P_{act}), *AverageReward* is computed as the average expected payoff, over all potential trustee decisions P_{act}, given $\sigma_{agg,err}$:

$$AverageReward = \int_{P_{act,min}}^{P_{act,max}} \left(PDF_{P_{act}}\left(P_{act}\right)\right)\left(Reward\left(P_{act}\right)\right) dP_{act}$$

$$AverageReward = \frac{1}{P_{act,max} - P_{act,min}} \int_{P_{act,min}}^{P_{act,max}} \left(P_{act} \int_0^{\infty} \left(\frac{e^{-\frac{\left(z-P_{act}\right)^2}{2\sigma_{agg,err}^2}}}{\sigma_{agg,err}\sqrt{2\pi}} \right) dz \right) dP_{act} \qquad \text{Eqn 42}$$

Solving symbolically for *AverageReward* is difficult; however an empirical approximation, calculated by discretizing the integrals in the *AverageReward* equation, is shown in Figure 4-7 (Figure 4-7 assumes $P_{act,max}$ = 10 and $P_{act,min}$ = -10). This approximation is closely fit by the following function:

$$AverageReward = \frac{P_{act,max}}{4}\left(1 - \left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}\right), \qquad \text{Eqn 43}$$

where γ equals 1000 (γ is determined by trial-and-error). Equation 43 is valid only for cases in which $P_{act,max} = -P_{act,min}$. In Section 4.1.5, a more general form of this equation, valid for all $P_{act,min}$ and $P_{act,max}$ is introduced, and the derivation of Equation 43 is explained.

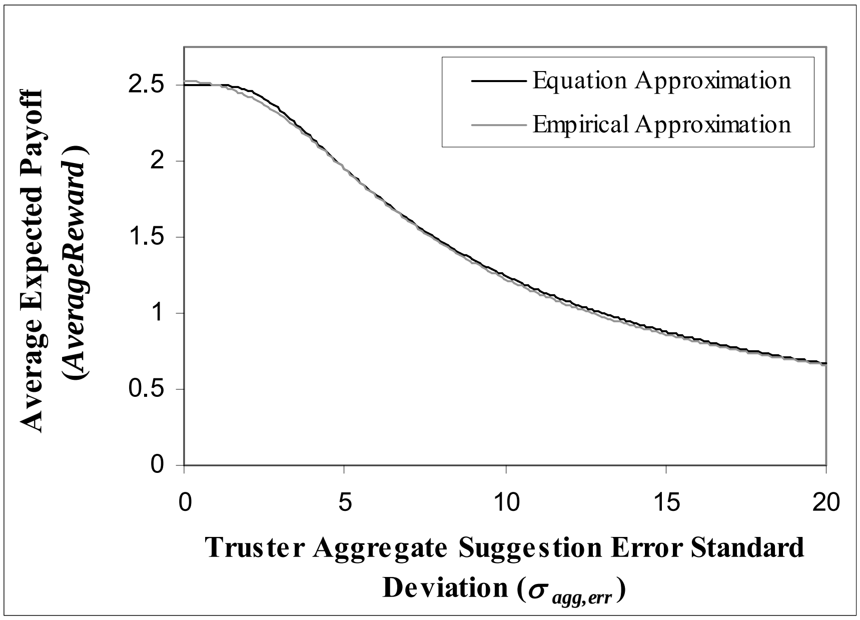


Figure 4-7. Truster average expected payoff (*AverageReward*), as a function of the truster's aggregate suggestion error standard deviation ($\sigma_{agg,err}$), defined by Equation 42. Both an empirical approximation and Equation 43's approximation of Equation 42 are shown. $P_{act,min}$ = -10 and $P_{act,max}$ = 10.

As shown in Figure 4-7, when $\sigma_{agg,err} = 0$ (the aggregate suggestion is an exact prediction), the average payoff received by following the aggregate suggestion is the maximum possible:

$$AverageReward_{max} = AverageReward\left(\sigma_{agg,err} = 0\right)$$

$$AverageReward_{max} = \frac{P_{act,max}}{4}\left(1-\left(\frac{0}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\cdot 0}}\right)$$

$$AverageReward_{max} = \frac{P_{act,max}}{4}\left(1-0\right)$$

$$AverageReward_{max} = \frac{P_{act,max}}{4} \qquad \text{Eqn 44}$$

This calculation is consistent with Figure 4-6 (and Figure 4-1c), which calculates *AverageReward* when $\sigma_{agg,err}$ = 0 as the triangular area in Figure 4-1c divided by the range $P_{act,min}$ to $P_{act,max}$:

$$AverageReward_{max} = \frac{\frac{1}{2}P_{act,max}^2}{P_{act,max} - P_{act,min}}$$

$$AverageReward_{max} = \frac{P_{act,max}^2}{2\left(2P_{act,max}\right)} \text{ (since } P_{act,max} = -P_{act,min}\text{)}$$

$$AverageReward_{max} = \frac{P_{act,max}}{4}.$$

Conversely, as $\sigma_{agg,err}$ approaches infinity (the aggregate suggestion is a random prediction), the average payoff received by following the aggregate suggestion is:

$$AverageReward_{min} = AverageReward\left(\sigma_{agg,err} = \infty\right)$$

$$AverageReward_{min} = \frac{P_{act,max}}{4}\left(1 - \left(\frac{\infty}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\cdot\infty}}\right)$$

$$AverageReward_{min} = \frac{P_{act,max}}{4}\left(1-1\right)$$

$$AverageReward_{min} = 0.$$

This calculation is consistent with Figure 4-6 (and Figure 4-2c), which calculates *AverageReward* when $\sigma_{agg,err} = \infty$ as the difference in triangular areas Figure 4-2c divided by the range $P_{act,min}$ to $P_{act,max}$:

$$AverageReward_{min} = \left(\frac{1}{2}\left(P_{act,max}\right)\left(\frac{1}{2}P_{act,max}\right)\right) - \left(\frac{1}{2}\left(P_{act,min}\right)\left(\frac{1}{2}P_{act,min}\right)\right)$$

$$AverageReward_{min} = \frac{P_{act,max}^2}{4} - \frac{P_{act,min}^2}{4}$$

$$AverageReward_{min} = 0 \text{ (since } P_{act,max} = -P_{act,min}\text{)}.$$

It is important to remember that Equation 43 assumes trustee decisions are uniformly distributed between $P_{act,max}$ = 10 and $P_{act,min}$ = -10; as discussed later in Section 4.1.5, other distributions of trustee decisions yield different functions for *AverageReward* in terms of $\sigma_{agg,err}$. For example, when trustee decisions are uniformly distributed with larger values of $P_{act,max}$ (in proportion to $P_{act,min}$), *AverageReward* is larger for a given $\sigma_{agg,err}$, since trustees yield a higher payoff, P_{act}, on average.

4.1.3 REPUTATION SCENARIOS

Figure 4-7 describes the relationship between 1) the error, $\sigma_{agg,err}$, of an aggregate suggestion and 2) the expected payoff, *AverageReward*, from a transaction for which the truster bases its trusting decision on that aggregate suggestion. This relationship is necessary for Adaptive Cost Selection to gauge the worth of purchasing reputations with the goal of improving aggregate suggestion accuracy (decreasing $\sigma_{agg,err}$). To do so, several reputation purchasing scenarios (lists of which reputations to purchase) are created, and the expected error standard deviation, $\sigma_{agg,err}$, of the aggregate suggestion is computed for each. To create these scenarios, reputation providers are ranked according to accuracy of past reputations (in terms of $\sigma_{R_i,err}$, the error standard deviation of the reputations they provide about trustees similar to the trustee in question), with the reasoning that the truster should purchase reputations in order of least to greatest error standard deviation ($\sigma_{R_i,err}$).

Note that the following discussion examines reputation provider accuracy in terms of $\sigma_{R_i,err}$ instead of $\sigma_{R_i,sug}$. Equation 5 in Section 3.1.4 demonstrates that, for any trust model, both σ_{sug} (the standard deviation of the model's suggestion distribution) and σ_{beh} (the standard deviation of the trustee's behavior distribution) contribute to σ_{err} (the standard deviation of the model's error distribution). However, this analysis of Adaptive Cost Selection assumes the case in which reputation-based modeling is most advantageous: one-time transaction opportunities with numerous potential trustee's ($m \leq 1$), as opposed to numerous transaction opportunities with the same trustee (large m). Therefore, any given trustee's σ_{beh} can be assumed zero, since the truster does not transact with the trustee enough times to be concerned about the trustee's behavior distribution. As a result, $\sigma_{err} = \sigma_{sug}$ (more specifically, $\sigma_{R_i,err} = \sigma_{R_i,sug}$) is assumed.

A scenario s_n is defined as a case in which reputations are purchased from the n reputation providers with lowest $\sigma_{R_i,err}$. Table 4-1 illustrates example scenarios for a set of five potential reputation providers. Columns 1-3 in Table 4-1 show scenario numbers (Column 1), with reputation providers (Column 2) sorted in order of ascending $\sigma_{R_i,err}$ (Column 3). The scenario table enumerates the reputation providers whose reputations would be purchased in each scenario s_n (Column 4).

Table 4-1. Example scenario table showing computation of *MarginalReward* for reputations from each in a set of five potential reputation providers: R_1, R_2, R_3, R_4, and R_5.

Scenario s_n	**Reputation Provider n**	$\sigma_{R_n,err}$	**Reputation Providers in s_n**	**Weights ω_n**	$\sigma_{agg,err}(s_n)$	***Average Reward* of s_n**	***Marginal Reward* of R_n**
s_0	—	—	{}	—	—	0.00	0.00
s_1	R_1	5.0	$\{R_1\}$	$\omega_1 = 1.00$	5.00	1.95	1.95
s_2	R_2	5.1	$\{R_1, R_2\}$	$\omega_1 = 0.51$ $\omega_2 = 0.49$	3.57	2.23	0.28
s_3	R_3	5.2	$\{R_1, R_2, R_3\}$	$\omega_1 = 0.35$ $\omega_2 = 0.33$ $\omega_3 = 0.32$	2.94	2.34	0.11
s_4	R_4	5.3	$\{R_1, R_2, R_3, R_4\}$	$\omega_1 = 0.26$ $\omega_2 = 0.25$ $\omega_3 = 0.24$ $\omega_4 = 0.24$	2.57	2.40	0.06
s_5	R_5	5.4	$\{R_1, R_2, R_3, R_4, R_5\}$	$\omega_1 = 0.22$ $\omega_2 = 0.21$ $\omega_3 = 0.20$ $\omega_4 = 0.19$ $\omega_5 = 0.19$	2.32	2.43	0.03
(*Col. 1*)	(*Col. 2*)	(*Col. 3*)	(*Col. 4*)	(*Col. 5*)	(*Col. 6*)	(*Col. 7*)	(*Col. 8*)

For each scenario, weights are calculated for the reputation of each included provider according to Adaptive Trust Modeling (Equation 15 in Section 3.3.2), as shown in Column 5. Next, the error standard deviation $\sigma_{agg,err}(s_n)$, of the hypothetical aggregate suggestion for each scenario is computed according to Equation 38 in Section 3.3.2

(Column 6). Using Equation 43 in Section 4.1.2, the *AverageReward* value associated with each scenario's $\sigma_{agg,err}(s_n)$ is determined (Column 7). Finally, Column 8 shows *MarginalReward*(R_n), the estimated additional payoff contributed by purchasing a reputation from reputation provider R_n and incorporating that reputation into the aggregate suggestion, is computed as the incremental expected payoff from incorporating the one additional reputation (from reputation provider R_n):

$$MarginalReward\left(R_n\right) = AverageReward\left(\sigma_{agg,err}\left(s_n\right)\right) - AverageReward\left(\sigma_{agg,err}\left(s_{n-1}\right)\right). \quad \text{Eqn 45}$$

For the purpose of calculating *MarginalReward* (R_1), a scenario, s_0, is included in which no reputations are purchased. As a result,

$$\sigma_{agg,err}\left(s_0\right) = \infty,$$

since the aggregate suggestion contains no information (the aggregate suggestion is an arbitrary guess). Therefore,

$$AverageReward\left(\sigma_{agg,err}\left(s_0\right)\right) = AverageReward_{min}$$

$$AverageReward\left(\sigma_{agg,err}\left(s_0\right)\right) = AverageReward\left(\sigma_{agg,err} = \infty\right).$$

When $P_{act,max} = 10$ and $P_{act,min} = -10$, $AverageReward\left(\sigma_{agg,err}\left(s_0\right)\right)$ is computed from Equation 43 in Section 4.1.2 as:

$$AverageReward\left(\sigma_{agg,err}\left(s_0\right)\right) = \frac{P_{act,max}}{4}\left(1-\left(\frac{\infty}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\cdot\infty}}\right)$$

$$AverageReward\left(\sigma_{agg,err}\left(s_0\right)\right) = 0.$$

If, instead of guessing arbitrarily, the truster adopts the policy of always declining transactions in the absence of suggestions, then

$$AverageReward\left(\sigma_{agg,err}\left(s_0\right)\right) = 0$$

since no transaction occurs. Note that when $P_{act,max} = 10$ and $P_{act,min} = -10$, $AverageReward\left(\sigma_{agg,err}\left(s_0\right)\right)$ is the same whether the truster guesses arbitrarily or declines to transact. However, when $P_{act,max} \neq -P_{act,min}$, arbitrary guessing may yield $AverageReward\left(\sigma_{agg,err}\left(s_0\right)\right)$ greater than or less than zero (these cases are examined further in Section 4.1.5).

Finally, Adaptive Cost Selection chooses the scenario s_n with the greatest value n such that

$$MarginalReward\left(R_i\right) > Cost\left(R_i\right) \quad \text{Eqn 46}$$

for all reputations R_i in s_n, where $Cost(R_i)$ is the cost the truster incurs purchasing R_i. Equation 46 assists the truster determining how many and which reputations to purchase given known values of $Cost(R_i)$. Further, Equation 46 serves as a tool for determining how much a truster is willing to pay for a given reputation when reputation prices are negotiable.

4.1.4 EXAMPLE: SELECTING SCENARIOS

This section presents an example of Adaptive Cost Selection put to use, showing how the variations in accuracy ($\sigma_{R_i,err}$) among the set of available reputation providers influence the accuracy of the aggregate suggestion ($\sigma_{agg,err}$), maximum reputation purchase price a truster is willing to pay, and the number of reputations purchased. For this purpose, Figure 4-8 shows the range of accuracy, in terms of reputation provider error standard deviation $\sigma_{R_i,err}$, for several example sets of available reputation providers. Each example set has a different value for the parameter β (β = 0.8, 1.0, 1.2, 2.0, and ∞), where

$$\sigma_{R_n,err} = \sigma_{R_1,err} \frac{\sum_{i=0}^{n-1} \beta^i}{\beta^{n-1}} \text{ for } n \geq 1. \quad \text{Eqn 47}$$

For example, when $\beta = \infty$, all reputation providers have the same error standard deviation of $\sigma_{R_1,err}$; therefore, ranking of reputation providers for the purpose of determining scenarios (as in Section 4.1.3) should be arbitrary (assuming the $\sigma_{R_i,err}$ values estimated by the truster are accurate approximations). In other words,

$$\sigma_{R_i,err} - \sigma_{R_{i-1},err} = 0 \text{ for } \beta = \infty.$$

When β = 1.0, error standard deviation increases by $\sigma_{R_1,err}$ for each successively less accurate reputation provider. As a result, the most accurate reputation provider (with

$\sigma_{R_1,err}$) is ranked first, followed by reputation providers with error standard deviations of $2\sigma_{R_1,err}$, $3\sigma_{R_1,err}$, $4\sigma_{R_1,err}$, etc., in order. In other words,

$$\sigma_{R_i,err} - \sigma_{R_{i-1},err} = \sigma_{R_1,err} \text{ for } \beta = 1.$$

When β < 1.0 (for example, β = 0.8 in Figure 4-8), error standard deviation for successively less accurate reputation providers increases at a rate that is greater than $\sigma_{R_1,err}$ and continuously increasing itself. Therefore,

$$\sigma_{R_i,err} - \sigma_{R_{i-1},err} > \sigma_{R_1,err} \text{ for } \beta < 1.$$

When β > 1.0 (for example, β = 1.2, 1.4, or 2.0 in Figure 4-8), error standard deviation for successively less accurate reputation providers increases at a rate that is less than $\sigma_{R_1,err}$ and slows as *i* increases, converging to an asymptotic error standard deviation given by

$$\lim_{i\to\infty}\left(\sigma_{R_i,err}\right) = \sigma_{R_1,err}\frac{\beta}{\beta-1} \text{ for } \beta > 1.$$

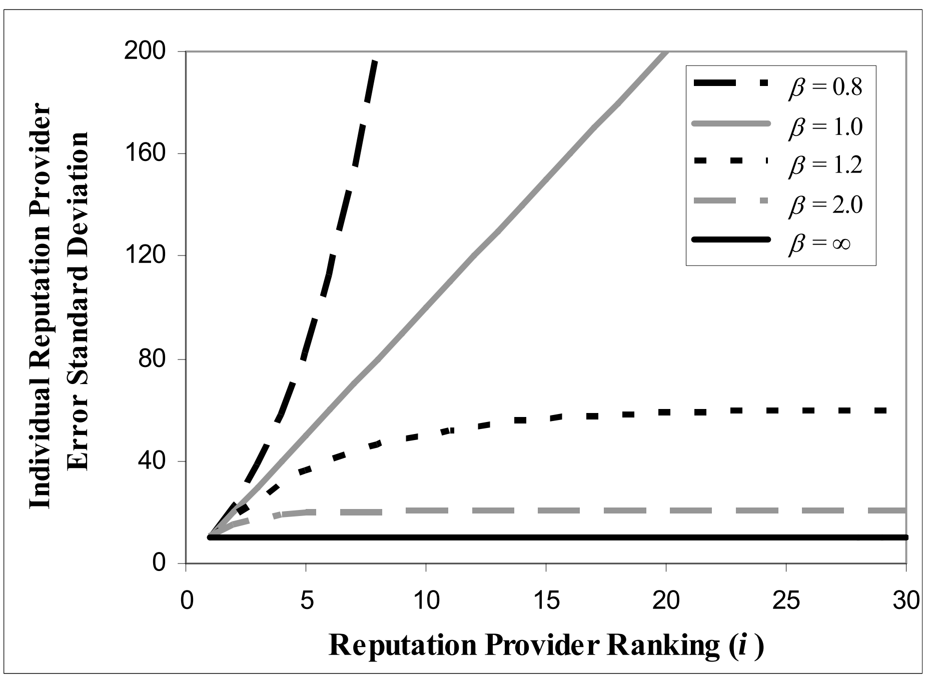


Figure 4-8. Reputation provider error standard deviations ($\sigma_{R_i,err}$, as computed by Equation 47 when $\sigma_{R_1,err}$ = 10) for reputation providers, by rank *i*, in a provider set for several values of β. For clarity, lines are continuous, though ranking *i* is discrete.

Figure 4-9 shows aggregate suggestion error standard deviations ($\sigma_{agg,err}$) for scenarios s_1 to s_{80} for each of five reputation provider sets defined by β (β = 0.8, 1.0, 1.2, 2.0, and ∞). The most accurate reputation provider, R_1, in each set has a standard deviation of $\sigma_{R_1,err}$ = 10. For each β, including additional reputations—regardless of the accuracy ($\sigma_{R_i,err}$) of the reputation provider—results in a decrease in $\sigma_{agg,err}$. When $\beta = \infty$ (all reputation providers have the same accuracy), $\sigma_{agg,err}$ decreases quickly with each additionally included reputation; when β is lower (each additionally included reputation provider is less accurate), the accuracy improvement attributed to each additional reputation is less. When β = 0.8, for example, additionally included reputations have so much error that they are assigned near-zero weights by Adaptive Trust Modeling; thus, $\sigma_{agg,err}$ reaches a minimum with only a few additionally included reputations and essentially decreases no further.

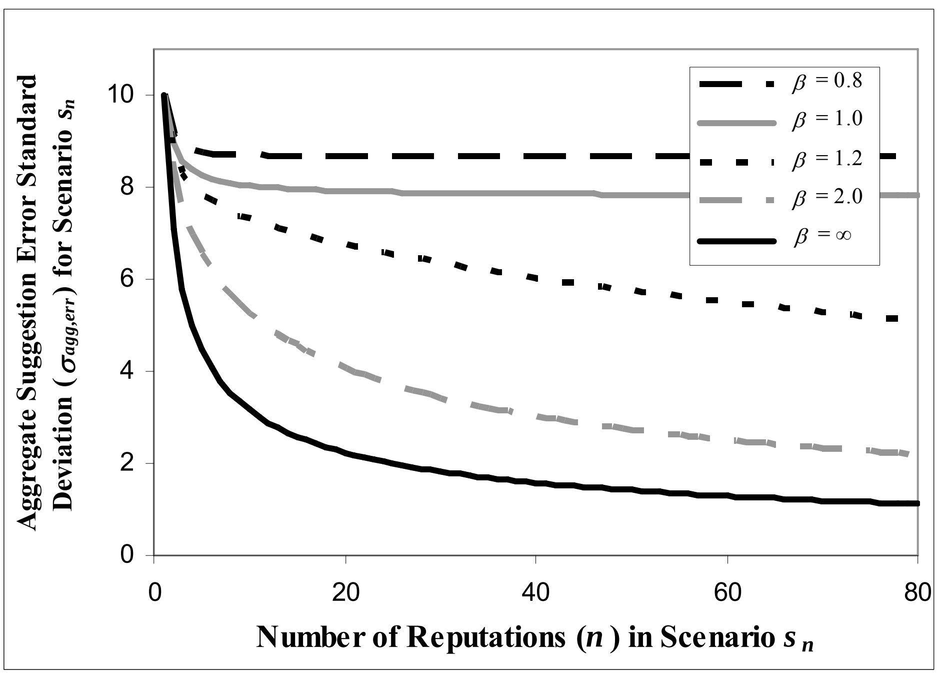


Figure 4-9. Aggregate suggestion error standard deviation ($\sigma_{agg,err}$) for scenario s_n (as computed theoretically by Adaptive Trust Modeling) by number of reputations n in scenario s_n for several values of β ($\sigma_{R_1,err}$ = 10). For clarity, lines are continuous, though n is discrete.

Including additional reputation suggestions from very inaccurate reputation providers never increases $\sigma_{agg,err}$ (assuming the truster models $\sigma_{R_i,err}$ values accurately), since Adaptive Trust Modeling assigns appropriately low weights for reputations from providers estimated to be inaccurate. Further, only when 1) one or more of the previously included reputations is given by a provider whose $\sigma_{R_i,err}$ is equal to zero, or 2) an additionally included reputation is given by a provider whose $\sigma_{R_i,err}$ is so high that it is weighted by Adaptive Trust Modeling as zero, does including an additional reputation cause $\sigma_{agg,err}$ to remain unchanged. In the former case, the reputation given by the provider whose $\sigma_{R_i,err}$ is zero is weighted by Adaptive Trust Modeling as one, while all other reputations are weighted as zero.

For comparison purposes, Figure 4-10 shows $\sigma_{agg,err}$ for the same five reputation provider sets (β = 0.8, 1.0, 1.2, 2.0, and ∞) when $\sigma_{agg,err}$ is computed by Simple Averaging (an extension of Equation 20 in Section 3.1.4 that accommodates more than two reputations) instead of Adaptive Trust Modeling. When $\beta = \infty$ (all reputation providers have the same level of accuracy), $\sigma_{agg,err}$ by s_n is the same for both Simple Averaging and Adaptive Trust Modeling, since both weighting techniques weight all reputations the same. However, for smaller β values (when $\beta \leq 1.0$ and each additionally included reputation suggestion is given by a provider whose $\sigma_{R_i,err}$ is significantly higher than that of the last included provider), additionally included reputations cause $\sigma_{agg,err}$ to increase when Simple Averaging is utilized. Comparing Figure 4-9 and Figure 4-10 shows the benefits of weighting reputations by Adaptive Trust Modeling, since Adaptive Trust Modeling can minimize the error introduced by later-included reputations with high error.

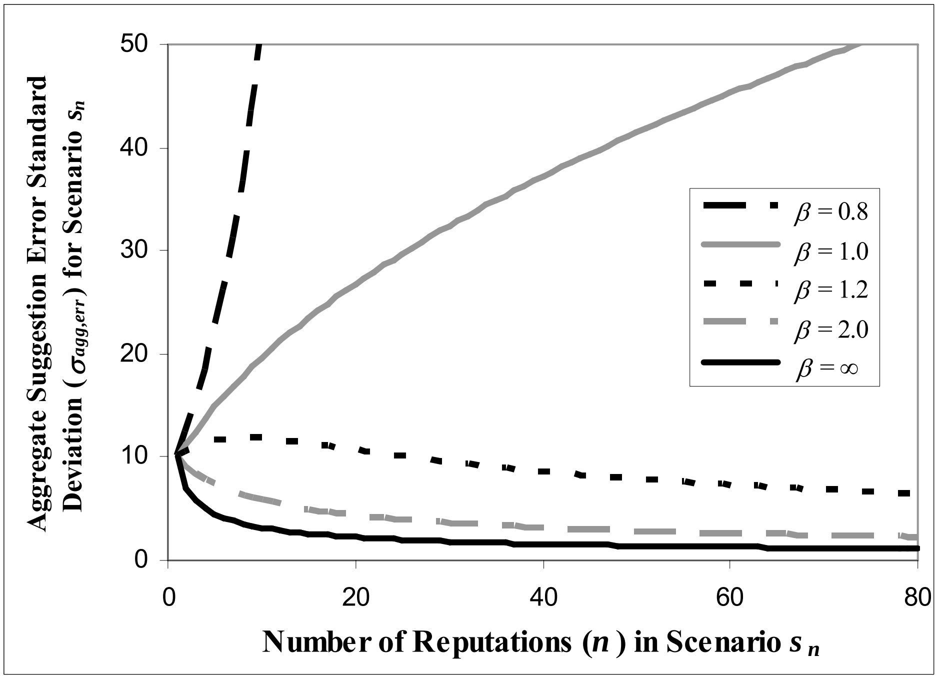


Figure 4-10. Aggregate suggestion error standard deviation ($\sigma_{agg,err}$) for scenario s_n, as computed theoretically by Simple Averaging, by number of reputations *n* in scenario s_n for several values of β ($\sigma_{R_1,err}$ = 10). For clarity, lines are continuous, though ranking *n* is discrete.

Figure 4-11 shows expected average payoff, *AverageReward*, for scenarios s_1 to s_{80} for each of five reputation provider sets defined by β (β = 0.8, 1.0, 1.2, 2.0, and ∞) when Adaptive Trust Modeling is used for weighting reputations ($P_{act,max}$ = 10 and $P_{act,min}$ = -10). As discussed previously, including additional reputations never results in an increase in $\sigma_{agg,err}$; likewise, including additional reputations never results in a decrease in *AverageReward*. When $\beta = \infty$, *AverageReward* quickly reaches $AverageReward_{max}$ as given by Equation 44 in Section 4.1.2. On the contrary, when β equals 0.8, *AverageReward* reaches a plateau far below $AverageReward_{max}$ with only a few reputations included. In this case, additionally included reputations have so much error that they are weighted by Adaptive Trust Modeling as zero; thus $\sigma_{agg,err}$ decreases (and *AverageReward* increases) no further.

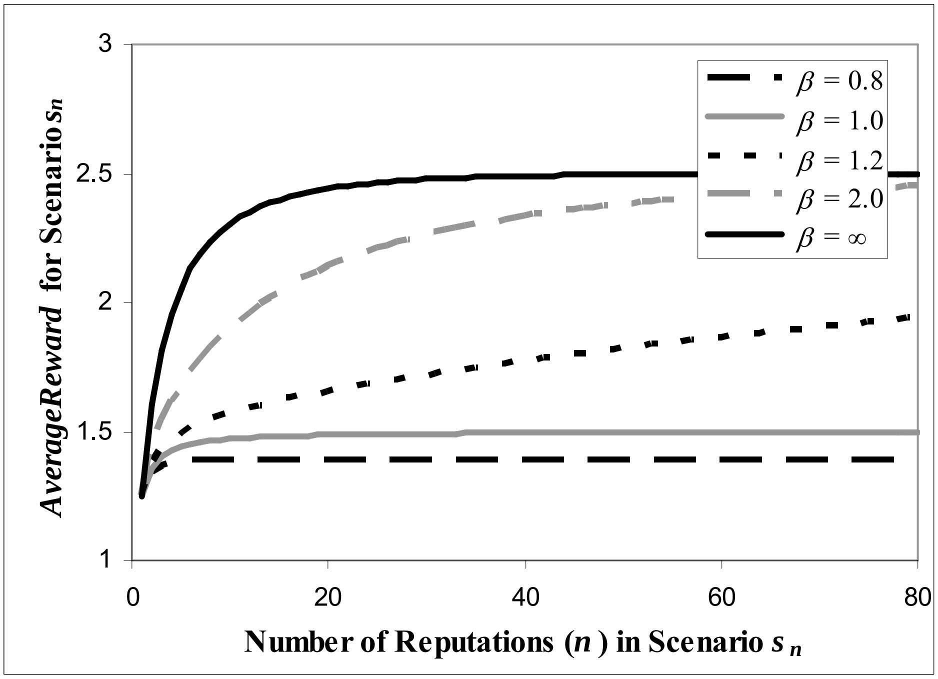


Figure 4-11. ***AverageReward*** **for scenario s_n, by reputation provider rank *n*, computed theoretically for several values of β ($\sigma_{R_1,err}$ = 10, $P_{act,max}$ = 10, and $P_{act,min}$ = -10). For clarity, lines are continuous, though *n* is discrete.**

Figure 4-12 shows expected incremental payoff, *MarginalReward*, for scenarios s_1 to s_{80} for each of five reputation provider sets defined by β (β = 0.8, 1.0, 1.2, 2.0, and ∞, $P_{act,max}$ = 10 and $P_{act,min}$ = -10). Expected *MarginalReward* for each additionally included reputation decreases quickly as the rank number (*i*) of that reputation increases; this decrease occurs faster for lower values of β, when $\sigma_{R_i,err}$ increases more quickly as rank number increases.

The expected *MarginalReward* function for $\beta = \infty$ initially decreases more slowly than the function for β = 2.0, yet crosses the β = 2.0 function later. This crossing occurs because though all reputations are equally accurate (in the $\beta = \infty$ set), only a few need to be included to produce a very small $\sigma_{agg,err}$ value. For the β = 2.0 set, each additionally included reputation is expected to be slightly less accurate than the last, but still contributing accuracy to the $\sigma_{agg,err}$ value (reputations have similar weights, as assigned by Adaptive Trust Modeling). As a result, reputations in the β = 2.0 set with higher rank numbers continue to achieve larger expected *MarginalReward* values while reputations in the $\beta = \infty$ set with the same rank numbers are weighted near zero by Adaptive Trust Modeling.

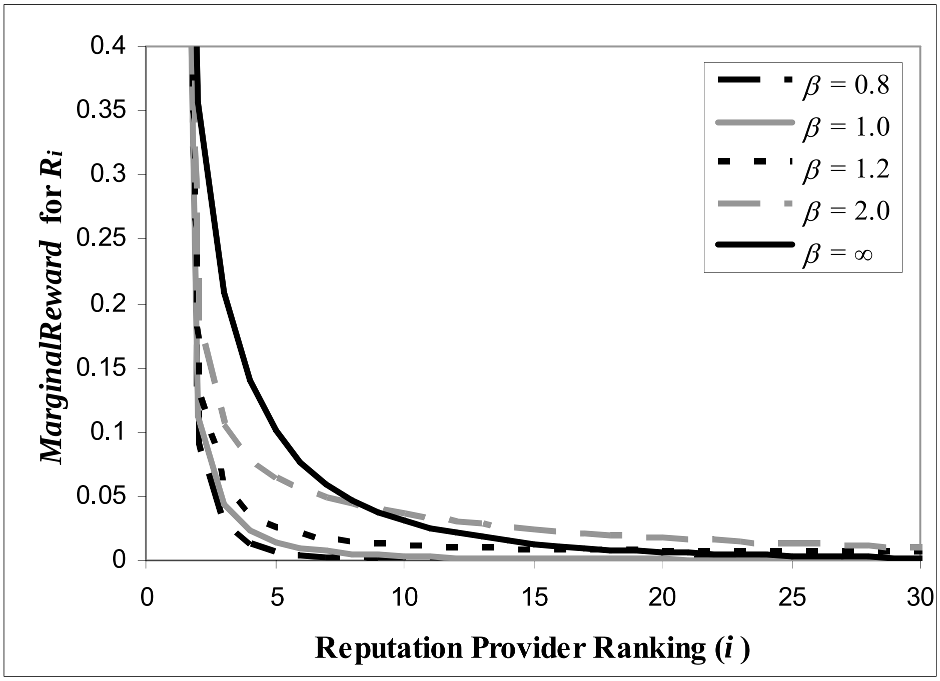


Figure 4-12. *MarginalReward* for reputation R_i, by ranking i, computed theoretically for several values of β ($\sigma_{R_1,err}$ = 10, $P_{act,max}$ = 10, and $P_{act,min}$ = -10). For clarity, lines are continuous, though ranking i is discrete.

Finally, from Equation 45 in Section 4.1.3, note that for all β,

$$MarginalReward\left(R_1\right) = AverageReward\left(\sigma_{agg,err}\left(s_1\right)\right) - AverageReward\left(\sigma_{agg,err}\left(s_0\right)\right)$$

$$MarginalReward\left(R_1\right) = \frac{P_{act,max}^2 - P_{act,min}^2\left(\frac{\sigma_{R_1,err}}{\gamma}\right)^{\frac{1}{\sigma_{R_1,err}}}}{2\left(P_{act,max} - P_{act,min}\right)} - 0$$

$$MarginalReward\left(R_1\right) = \frac{P_{act,max}^2 - P_{act,min}^2\left(\frac{\sigma_{R_1,err}}{\gamma}\right)^{\frac{1}{\sigma_{R_1,err}}}}{2\left(P_{act,max} - P_{act,min}\right)}.$$

Since the highest-ranking reputation providers in all example sets have equal error standard deviation ($\sigma_{R_1 err}$), regardless of β, expected *MarginalReward* for the highest-ranked reputation in each set is the same (out of range, therefore not shown, in Figure 4-12).

Figure 4-13 displays the stepwise function for determining scenario s_n (where n is the number of reputations to purchase, starting with the most accurate reputation provider) given reputation cost (cost for all reputations is assumed to be the same). For reference, reputation provider ranking (i) vs. expected *MarginalReward* (the inverse graph of Figure 4-12) is also plotted. In Figure 4-13, $\sigma_{R_1,err} = 10$, $P_{act,max} = 10$, and $P_{act,min} = -10$. For visual clarity, only the functions related to the $\beta = \infty$ example set are shown. Once a truster has computed a chart similar to Figure 4-13 based on the $\sigma_{R_i err}$ values for its potential reputation providers, the truster determines from the stepwise function the scenario s_n that corresponds to the reputation purchase price $Cost(R_i)$.

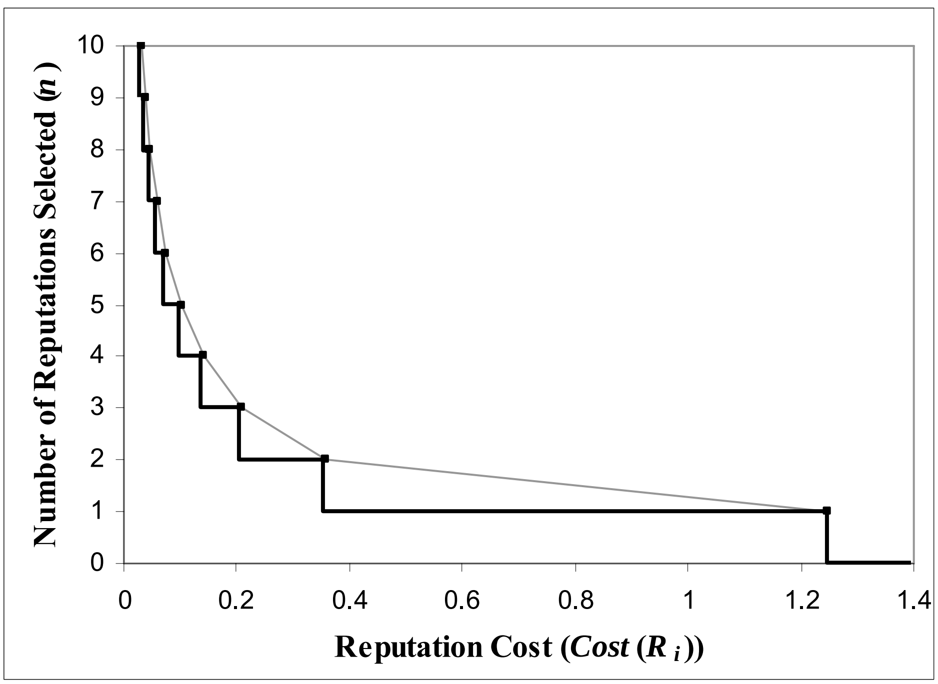


Figure 4-13. Optimal number of reputation providers selected (n) by the truster—yielding greatest aggregate suggestion accuracy for least reputation cost—computed theoretically as a function of reputation cost ($Cost(R_i)$). In this figure, $\beta = \infty$, $\sigma_{R_1,err} = 10$, $P_{act,max} = 10$, and $P_{act,min} = -10$.

While the experiments to be discussed in Section 4.2 assume all reputations incur the same $Cost(R_i)$, Adaptive Cost Selection's analysis of reputation *MarginalReward* enables trusters to negotiate with reputation providers the prices they are willing to pay for reputations, based on anticipated reputation accuracy. For example, a reputation that is expected to gain a greater *MarginalReward* is worth a higher price because it is expected to increase the accuracy of the aggregate suggestion more, resulting in significantly higher *AverageReward* than if it were not purchased.

Figure 4-14 charts a truster's expected net profit (*NetProfit*) from a transaction, computed as

$$\text{expected } NetProfit\left(s_n\right) = AverageReward\left(s_n\right) - \sum_{i=1}^{n} Cost\left(R_i\right), \qquad \text{Eqn 48}$$

a function of n (number of reputations to purchase) for several values of $Cost(R_i)$ (assuming $Cost(R_i)$ is the same for all reputations). When $Cost(R_i)$ is low, numerous reputations may be purchased to maximize *AverageReward*. However, when $Cost(R_i)$ is high, reputation purchase costs quickly outweigh higher *AverageReward* (associated with the aggregate suggestion's increased accuracy) as the number of purchased reputations increases. Note that the n values resulting in maximum *NetProfit* for given reputation cost ($Cost(R_i)$) in Figure 4-14 correspond to the n-vs.-*MarginalReward* data points in Figure 4-13.

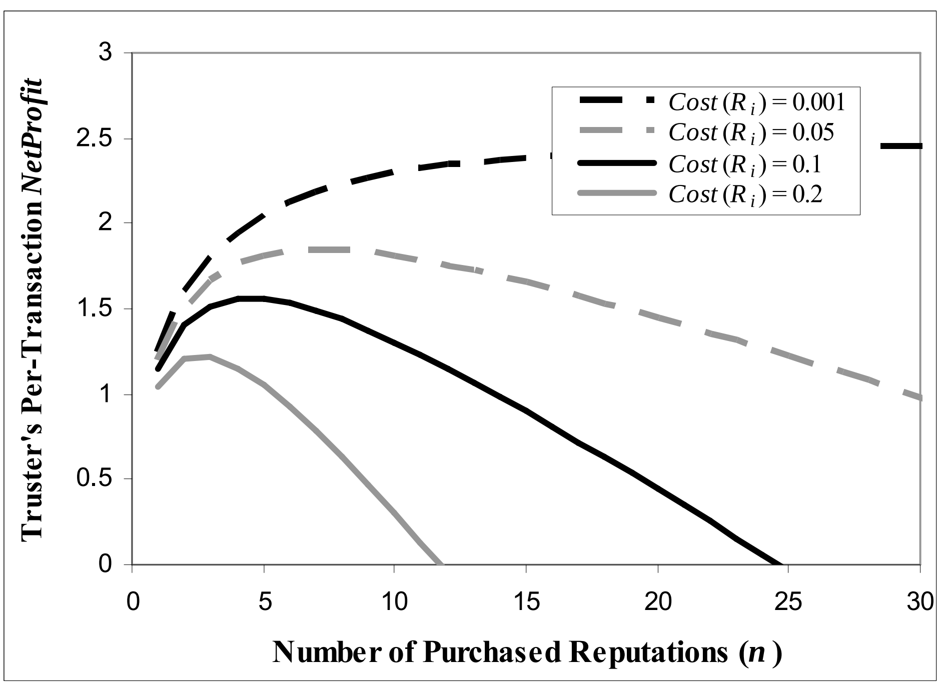


Figure 4-14. Truster's per-transaction *NetProfit*, computed theoretically as a function of number of purchased reputations n for several values of $Cost(R_i)$. In this figure, $\beta = \infty$ and $\sigma_{R_1,err} = 10$. For clarity, lines are continuous, though n is discrete.

Sections 4.1.1 through 4.1.4 explain the Adaptive Cost Selection algorithm for assessing the value of individual reputations to determine which reputations to purchase when cost is a factor. Adaptive Cost Selection can be extended to valuate experience-based trust information, as well. By estimating a single experience's impact to decrease a truster's experience-based model error standard deviation (and increases its approximated *AverageReward*), the experience's *MarginalReward* can be estimated, revealing the cost the truster should be willing to pay to acquire that experience. The cost of the experience is indirect, related to the time and potential transaction losses invested in obtaining the experience. Intuitively, humans realize the value of time and effort invested into building expertise based on experiences. This Adaptive Cost Selection analysis of experience-based trust information quantifies the value of experience.

4.1.5 ASSESSING RISK VIA *AVERAGEREWARD* FUNCTIONS

Section 4.1.2 introduces an equation for *AverageReward*, based on $P_{act,min}$ and $P_{act,max}$, that is valid when $P_{act,max} = -P_{act,min}$. This section introduces a general form of the *AverageReward* equation valid for all values of $P_{act,min}$ and $P_{act,max}$. More importantly, understanding the *AverageReward* function's dependency on $P_{act,min}$ and $P_{act,max}$—and the relationships among different *AverageReward* functions—reveals how *AverageReward* functions explain a truster's decision-making with regard to risk.

As a first step toward examining the relationship between *AverageReward* and risk, this section derives a general form of the *AverageReward* equation. Recall from Equation 42 that *AverageReward* is the integral of the *Reward* curve (Figure 4-6), for a given $\sigma_{agg,err}$,

$$Reward\left(P_{act}\right) = P_{act}\int_0^{\infty}\left(\frac{e^{-\frac{\left(z-P_{agg,sug}\right)^2}{2\sigma^2}}}{\sigma\sqrt{2\pi}}\right)dz\,, \qquad \text{Eqn 41}$$

divided by the range, $P_{act,max} - P_{act,min}$, over which trustee behavior is uniformly distributed:

$$AverageReward = \frac{1}{P_{act,max} - P_{act,min}} \int_{P_{act,min}}^{P_{act,max}} \left(P_{act} \int_0^{\infty} \left(\frac{e^{-\frac{(z-P_{act})^2}{2\sigma_{agg,err}^2}}}{\sigma_{agg,err}\sqrt{2\pi}} \right) dz \right) dP_{act} . \quad \text{Eqn 42}$$

Note that this research assumes P_{act} is uniformly distributed to enable this discussion to outline a single set of derivations for *AverageReward* equations (however, *AverageReward* for other distributions of P_{act} can be approximated, as well). The negative portion (when $P_{act,min} \leq P_{act} \leq 0$) of the *Reward* integral is approximated by:

$$\int_{P_{act,min}}^{0} \left(Reward\left(P_{act}\right)\right) dP_{act} = -\frac{P_{act,min}^2}{4} \left(-\frac{\sigma_{agg,err}}{\gamma P_{act,min}} \right)^{\frac{-P_{act,min}}{10\sigma_{agg,err}}}$$

where $\gamma = 1000$ (as determined by trial-and-error). The positive portion (when $0 \leq P_{act} \leq P_{act,max}$) of the *Reward* integral is approximated by:

$$\int_0^{P_{act,max}} \left(Reward\left(P_{act}\right)\right) dP_{act} = \frac{P_{act,max}^2}{2} - \frac{P_{act,max}^2}{4} \left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}} \right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}$$

$$\int_0^{P_{act,max}} \left(Reward\left(P_{act}\right)\right) dP_{act} = \frac{P_{act,max}^2}{4} \left(2 - \left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}} \right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}} \right).$$

Therefore, *AverageReward*, when $P_{act,min} < 0$ and $P_{act,max} = 0$, is given by:

$$AverageReward = \frac{\int_{P_{act,min}}^{0} \left(Reward\left(P_{act}\right)\right) dP_{act}}{0 - P_{act,min}}$$

$$AverageReward = \frac{-\frac{P_{act,min}^2}{4} \left(-\frac{\sigma_{agg,err}}{\gamma P_{act,min}} \right)^{\frac{-P_{act,min}}{10\sigma_{agg,err}}}}{0 - P_{act,min}}$$

$$AverageReward = \frac{P_{act,min}}{4} \left(-\frac{\sigma_{agg,err}}{\gamma P_{act,min}} \right)^{\frac{-P_{act,min}}{10\sigma_{agg,err}}} . \quad \text{Eqn 49}$$

Similarly, *AverageReward*, when $P_{act,min} = 0$ and $P_{act,max} > 0$, is given by:

$$AverageReward = \frac{\int_0^{P_{act,max}} \left(Reward\left(P_{act}\right)\right) dP_{act}}{P_{act,max} - 0}$$

$$AverageReward = \frac{\frac{P_{act,max}^2}{4}\left(2-\left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}\right)}{P_{act,max}-0}$$

$$AverageReward = \frac{P_{act,max}}{4}\left(2-\left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}\right). \qquad \text{Eqn 50}$$

When $P_{act,min} < 0 < P_{act,max}$, *AverageReward* is given by:

$$AverageReward = \frac{\int_{P_{act,min}}^{P_{act,max}}\left(Reward\left(P_{act}\right)\right)dP_{act}}{P_{act,max}-P_{act,min}}$$

$$AverageReward = \frac{\int_{P_{act,min}}^{0}\left(Reward\left(P_{act}\right)\right)dP_{act}+\int_{0}^{P_{act,max}}\left(Reward\left(P_{act}\right)\right)dP_{act}}{P_{act,max}-P_{act,min}}$$

$$AverageReward = \frac{-\frac{P_{act,min}^2}{4}\left(-\frac{\sigma_{agg,err}}{\gamma P_{act,min}}\right)^{\frac{-P_{act,min}}{10\sigma_{agg,err}}}+\frac{P_{act,max}^2}{4}\left(2-\left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}\right)}{P_{act,max}-P_{act,min}}. \qquad \text{Eqn 51}$$

The special case in which $P_{act,max} = -P_{act,min}$ yields the *AverageReward* equation given by Equation 43 in Section 4.1.2:

$$AverageReward = \frac{-\frac{P_{act,max}^2}{4}\left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}+\frac{P_{act,max}^2}{4}\left(2-\left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}\right)}{2P_{act,max}}$$

$$AverageReward = \frac{\frac{P_{act,max}^2}{4}\left(2-2\left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}\right)}{2P_{act,max}}$$

$$AverageReward = \frac{\frac{P_{act,max}^2}{2}\left(1-\left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}\right)}{2P_{act,max}}$$

$$AverageReward = \frac{P_{act,max}}{4}\left(1-\left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}\right). \qquad \text{Eqn 52}$$

When $0 < P_{act,min} < P_{act,max}$, *AverageReward* is given by:

$$AverageReward = \frac{\int_{P_{act,min}}^{P_{act,max}} \left(Reward\left(P_{act}\right)\right) dP_{act}}{P_{act,max} - P_{act,min}}$$

$$AverageReward = \frac{\int_{0}^{P_{act,max}} \left(Reward\left(P_{act}\right)\right) dP_{act} - \int_{0}^{P_{act,min}} \left(Reward\left(P_{act}\right)\right) dP_{act}}{P_{act,max} - P_{act,min}}$$

$$AverageReward = \frac{\frac{P_{act,max}^2}{4}\left(2-\left(\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{P_{act,max}}{10\sigma_{agg,err}}}\right) - \frac{P_{act,min}^2}{4}\left(2-\left(\frac{\sigma_{agg,err}}{\gamma P_{act,min}}\right)^{\frac{P_{act,min}}{10\sigma_{agg,err}}}\right)}{P_{act,max} - P_{act,min}}.$$

Eqn 53

Similarly, when $P_{act,min} < P_{act,max} < 0$, *AverageReward* is given by:

$$AverageReward = \frac{\int_{P_{act,min}}^{P_{act,max}} \left(Reward\left(P_{act}\right)\right) dP_{act}}{P_{act,max} - P_{act,min}}$$

$$AverageReward = \frac{\int_{P_{act,min}}^{0} \left(Reward\left(P_{act}\right)\right) dP_{act} - \int_{P_{act,max}}^{0} \left(Reward\left(P_{act}\right)\right) dP_{act}}{P_{act,max} - P_{act,min}}$$

$$AverageReward = \frac{-\frac{P_{act,min}^2}{4}\left(-\frac{\sigma_{agg,err}}{\gamma P_{act,min}}\right)^{\frac{-P_{act,min}}{10\sigma_{agg,err}}} + \frac{P_{act,max}^2}{4}\left(-\frac{\sigma_{agg,err}}{\gamma P_{act,max}}\right)^{\frac{-P_{act,max}}{10\sigma_{agg,err}}}}{P_{act,max} - P_{act,min}}.$$

Eqn 54

Understanding *AverageReward* enables a truster to account for risk when making trust-based decisions. The Stanford Encyclopedia of Philosophy provides one definition of risk as "the statistical expectation value of an unwanted event which may or may not occur" [Stanford Encyclopedia of Philosophy, 2007]. Risk may be considered to have two components: uncertainty and exposure [Holton, 2004]. The truster's aggregate suggestion error ($\sigma_{agg,err}$) determines the truster's uncertainty about the value of the resource the trustee will choose to provide (from Section 3.1.1, $P_{e,r,act}$), which translates to uncertainty about the truster's net payoff from the transaction, P_{act}, recalling, from Section 3.1.1:

$$P_{act} = P_{e,r,act} - P_{r,r}. \qquad \text{Eqn 55}$$

Exposure magnitude is determined by the truster's initial outlay (from Section 3.1.1, $P_{r,r}$), and is given by the truster's worst case net transaction payoff, $P_{act,min}$, when $P_{e,r,act}$ equals zero:

$$P_{act,min} = P_{act}(P_{e,r,act} = 0) = -P_{r,r}.$$

Computing *AverageReward* for this worst case, when trustees are always as untrustworthy as possible by delivering resource of value $P_{e,r,act} = 0$ ($P_{act,min} = P_{act,max} = -P_{r,r}$):

$$AverageReward = \frac{\int_{P_{act,min}}^{P_{act,max}} \left(Reward\left(P_{act}\right)\right) dP_{act}}{P_{act,max} - P_{act,min}}$$

$$AverageReward = \frac{\int_{P_{act,min}}^{P_{act,min}} \left(Reward\left(P_{act}\right)\right) dP_{act}}{dP_{act}}$$

$$AverageReward = Reward\left(P_{act,min}\right)$$

$$AverageReward = Prob\left(T \mid P_{act,min}\right) P_{act,min}.$$

When $\sigma_{agg,err} = \infty$ (truster has no suggestions available and has the highest possible uncertainty about the transaction outcome), $Prob(T|P_{act,min}) = 0.5$. Therefore, in the worst possible case ($P_{act} = P_{act,min}$ and $\sigma_{agg,err} = \infty$):

$$AverageReward = 0.5 \cdot P_{act,min}$$

When the truster has no suggestions about the trustworthiness of potential trustees ($\sigma_{agg,err} = \infty$), the truster can decrease its risk by reducing its outlay ($P_{r,r}$ and therefore, the magnitude of $P_{act,min}$). Figure 4-15 demonstrates an example in which the truster assumes the worst case ($P_{act} = P_{act,min} = -P_{r,r}$), deciding on a small outlay, $P_{r,r} = 3$ to reduce the magnitude of $P_{act,min}$. *AverageReward* in this case is shown by Point 1 in Figure 4-15a. Once the truster has conducted transactions with trustees in the system, the truster can begin to model the distribution of P_{act} over all potential trustees (instead of assuming the worst case $P_{act} = P_{act,min} = -P_{r,r}$), selecting the most appropriate *AverageReward* function (for example, U[-3, 3], shown by Point 2 in Figure 4-15a). Further, if the truster can obtain many (experience- or reputation-based) suggestions about a trustee, the truster will have developed a low $\sigma_{agg,err}$ about that trustee, resulting in a higher *AverageReward* due to leftward movement along the *AverageReward* curve (Point 3 in Figure 4-15a). Upon identifying the most appropriate *AverageReward* function and obtaining suggestions about specific trustees, the truster can begin to increase the magnitude of its transactions (shown by the larger outlay of $P_{r,r}$ = 10 at Point 4 in Figure 4-15b). If the truster does not choose to reduce its outlay, it is initially subjected to the greater risk associated with transactions of larger magnitude (as shown by Point 5 in Figure 4-15b).

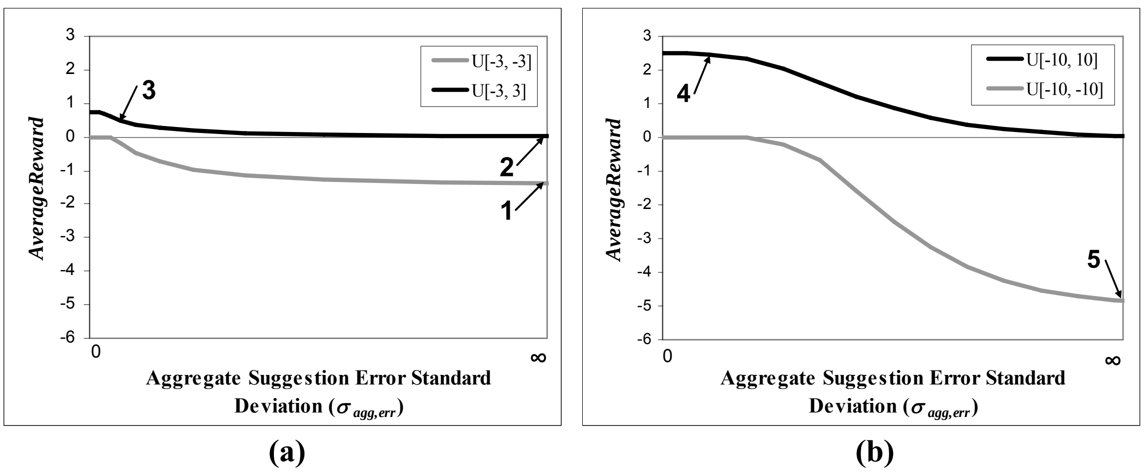


Figure 4-15. *AverageReward* as a function of aggregate suggestion error standard deviation ($\sigma_{agg,err}$) when the truster's transaction outlay $P_{r,r}$ equals (a) 3 and (b) 10.

The truster's strategy of reducing outlay while building trust agrees with intuitive human trusting behavior. When a human truster approaches a trustee (or system of trustees) for the first time, the truster will often gain experience with the trustee (or set of trustees) by conducting transactions of relatively small value. As a result, the truster protects itself from high risk transactions while gaining trust information about the trustee (or set of trustees). Once the truster feels confident about the trustworthiness of the trustee and $\sigma_{agg,err}$ is low (or set of trustees and the distribution of P_{act} is closely approximated), the truster may choose to trust with regard to a transaction of high value, since trust has been built up over time [Bennis, et al., 1964]. However, it should be noted that waiting to increase transaction magnitude until trust estimates are more accurate does not guarantee the truster avoids risk. Strategically untrustworthy trustees may intentionally act trustworthy during small-value transactions, building up trust with the intent to cheat the truster in a high-value transaction.

The magnitude of a truster's transaction (determined by its outlay $P_{r,r}$) also influences the priority the truster places on obtaining trust information about potential trustees, in terms of the $Cost(R_i)$ the truster is willing to pay. Figure 4-16 shows *AverageReward* as a function of $\sigma_{agg,err}$ when $P_{act,max} = -P_{act,min}$ and $P_{act,max} = 1, 3, 5$, and 10. When $P_{act,max} = -P_{act,min}$, larger $P_{act,max}$ values achieve larger *AverageReward* values for a given level of aggregate suggestion error ($\sigma_{agg,err}$). Figure 4-17 shows the corresponding *MarginalReward* as a function of number of combined reputation suggestions (scenario s_n), assuming all reputation suggestions have error standard deviations $\sigma_{R_i,err} = 10$ (that is, $\sigma_{R_1,err} = 10$ and $\beta = \infty$, according to Equation 47 in Section 4.1.4). Note that the *MarginalReward* function for $P_{act,max} = 10$ in Figure 4-17 represents the same *MarginalReward* function for $\beta = \infty$, in Figure 4-12 of Section 4.1.4. Since a truster using Adaptive Cost Selection will pay at most the *MarginalReward* of a reputation to purchase that reputation, Figure 4-17 shows that a truster is willing to pay more for reputations when the "stakes" are higher (i.e., the magnitudes of potential payoff $P_{act,max}$ and loss $P_{act,min}$ are greater).

The concept of investing more to estimate the outcome of larger-magnitude transactions is intuitive. For example, if the truster is a potential homebuyer, he is likely to invest a large amount of time and money acquiring trust information that is both experience-based (attending open houses) and reputation-based (hiring an inspector). Similarly, if the truster is a consumer planning to buy an expensive new automobile, he will usually invest significantly by test driving vehicles and purchasing referrals, such as a new car buying guide. On the other hand, when the truster is an individual deciding on a restaurant at which to dine, he will usually invest considerably less time and money into deciding on a restaurant, perhaps simply checking internet reviews or just selecting a restaurant with little thought.

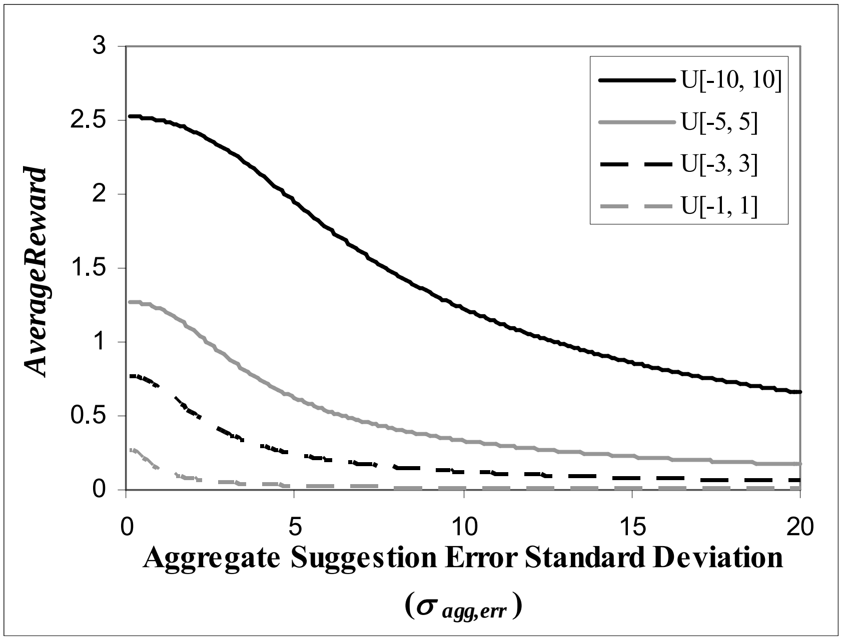


Figure 4-16. *AverageReward* as a function of aggregate suggestion error standard deviation ($\sigma_{agg,err}$) when $P_{act,max}$ = -$P_{act,min}$ and $P_{act,max}$ = 1, 3, 5, and 10.

For a given $P_{act,min}$ and $P_{act,max}$ where $P_{act,max}$ = -$P_{act,min}$, the *AverageReward* functions describing trustee behavior distributions of 1) $U[P_{act,min}, P_{act,max}]$, 2) $U[P_{act,min}, 0]$, and 3) $U[0, P_{act,max}]$, are parallel (as shown in Figure 4-18 for the case in which $P_{act,max}$ = 10). Therefore, *MarginalReward* functions, as shown in Figure 4-17, are the same for each of the three cases (the truster achieves the same increase in *AverageReward* for a given reputation in each case). As a result, in these three cases, the amount a truster invests in acquiring reputations depends only on the magnitude of the transaction ($P_{act,min}$ and $P_{act,max}$), not on the overall level of trustworthiness within the pool of potential trustees (which may not be true when compared against other distributions of P_{act}, such as U[-10, -9], for example).

The whole of this research assumes the truster's decisions are Boolean (trust vs. not-trust) and the truster's outlay value, $P_{r,r}$, is fixed. However, if the truster is enabled to choose the magnitude of $P_{r,r}$, the truster can decrease its risk by only conducting small-value transactions when the truster has no trust information about trustees ($_{agg,err} = \infty$). When trust information is available (either experience- or reputation-based suggestions), the truster can increase the magnitude of its outlay, since trust information increases the truster's certainty of the transaction outcome. Further, a truster's willingness to pay for reputations is directly related to the magnitude of the truster's outlay; the truster is willing to pay more for reputations when the value of the transaction is higher.

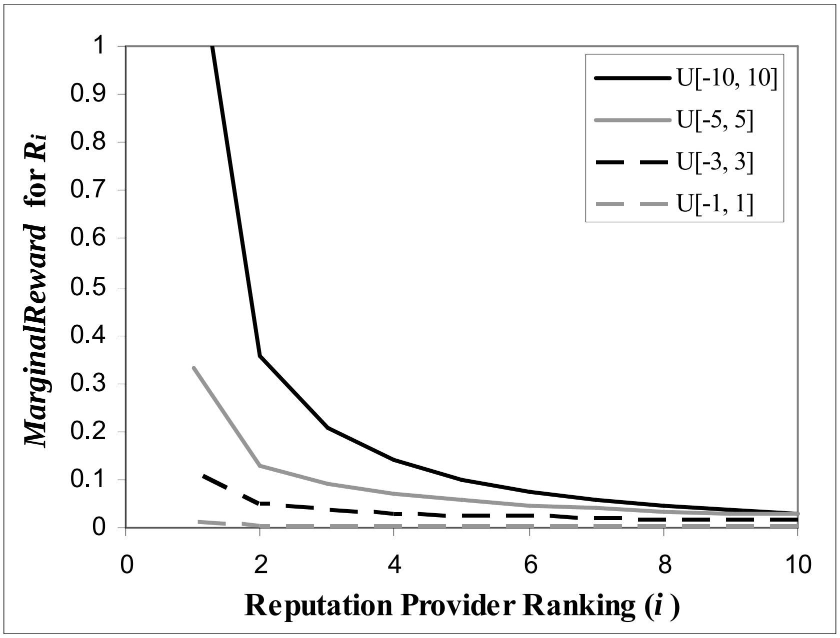


Figure 4-17. ***MarginalReward*** **of reputation** ***i*** **as a function of** ***n*** **when** $P_{act,max} = -P_{act,min}$ **and** $P_{act,max} = 1$**, 3, 5, and 10.**

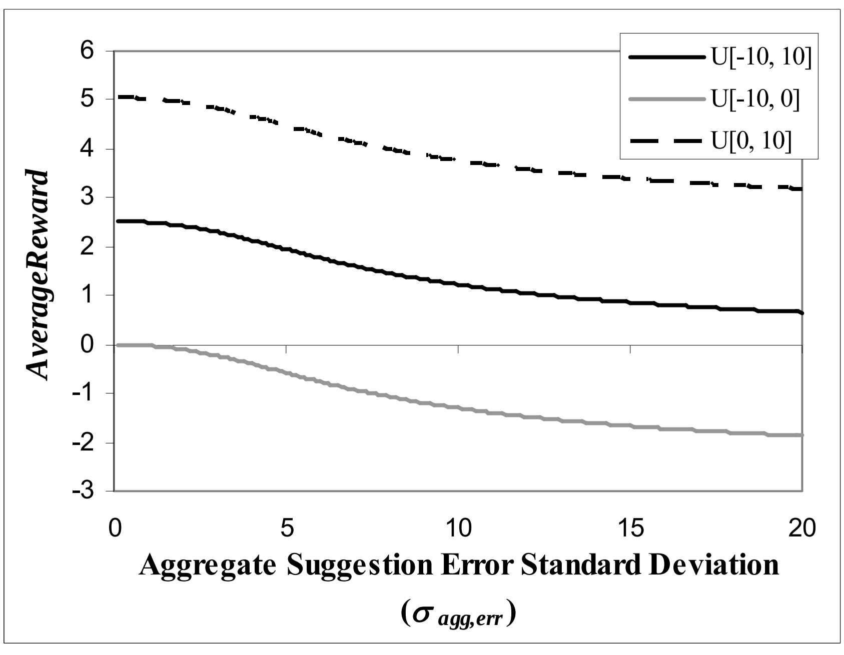


Figure 4-18. ***AverageReward*** **as a function of aggregate suggestion error standard deviation (**$\sigma_{agg,err}$**) when the distribution of** P_{act} **over all potential trustees is U[-10, 10], U[-10, 0], and U[0, 10].**

This section refutes Misconception 6 from Section 1.4: *A truster should always rely on reputation-based modeling when it has no experience with a trustee.* More accurately, a truster is more likely to purchase reputations when considering a high-value transaction simply because each acquired reputation is worth more (has a higher *MarginalReward*). However, if the truster has access to an accurate, no-cost experience-based model, the truster is likely to utilize its experiences, as well, regardless of the transaction magnitude. When considering low-value transactions, reputations may be too expensive in relation to the transaction magnitude; therefore, a truster may be forced to rely on experience-based modeling or no trust information at all. When a truster has no trust information, the truster's decision to trust anyway does not indicate a use of experience-based trust modeling. Rather, the decision to trust indicates the truster's threshold for risk is not exceeded by the low value of the transactions magnitude. However, the result of transaction may be observed by the truster and incorporated into its experience-based model for use regarding subsequent decisions.

4.2 Adaptive Cost Selection Evaluation

This section validates Adaptive Cost Selection, demonstrating that Adaptive Cost Selection achieves *NetProfit* (as defined by Equation 48 in Section 4.1.4) as high as the most profitable fixed-quantity reputation selection approach when the truster both does and does not have access to an experience-based trust model (Section 4.2.1). Section 4.2.2 shows that *NetProfit* decreases only slightly when the assumption of a priori knowledge of the trustees' P_{act} distribution is relaxed.

4.2.1 Adaptive Cost Selection vs. Fixed-Quantity Selection

An experiment is conducted to compare the Adaptive Cost Selection technique against static strategies which select fixed numbers of reputation providers. In this experiment, a single truster has access to ten reputation providers, each providing reputation suggestions according to $N(\mu_{R,sug}, \sigma_{R,sug})$, where $\mu_{R,sug} = P_{act}$ and $\sigma_{R,sug} = 10.0$, resulting in error distributions described by $N(\mu_{R,err}, \sigma_{R,err})$, where $\mu_{R,err} = 0$ and $\sigma_{R,err} = \sigma_{R,sug}$. In this experiment, the truster is assumed to have no experience-based model so the problem of selecting reputations can be isolated (later, a second experiment in this section incorporates the truster's experience-based model). All reputation providers have the same accuracy ($\beta = \infty$) because, as indicated by Figure 4-12 in Section 4.1.4, more similarity (very high β value, from Equation 47 in Section 4.1.4) among the accuracies of reputation providers makes more difficult the truster's decision concerning how many reputation providers to select. On the contrary, a set of reputation providers with a wide range of accuracy (very low β value) often requires only a trivial solution from the truster: select only the single most accurate reputation provider. P_{act} represents the actual outcome of trustee behavior (truster's net payoff) for the transaction in question. P_{act} values over all transaction opportunities are uniformly distributed between $P_{act,min}$ = -10.0 and $P_{act,max}$ = 10.0 to simulate the truster's encounter with a new trustee in each transaction opportunity. The truster's Adaptive Cost Selection technique uses the corresponding computation of *AverageReward* given by Equation 43 in Section 4.1.2, which assumes uniform distribution of P_{act}, with $P_{act,min}$ = -10.0 and $P_{act,max}$ = 10.0 (Section 4.2.2 relaxes the assumption that the distribution of P_{act} is known a priori by the truster). Results from 20 runs, each consisting of 2000 transaction opportunities with unique trustees, are averaged. The experiment compares the truster's average per-transaction profit (*NetProfit*, defined by Equation 48 in Section 4.1.4 as transaction earnings minus reputation costs) when the truster utilizes Adaptive Cost Selection vs. selecting a fixed quantity of the most accurate providers (scenarios s_1, s_4, s_6, s_8, or s_{10}).

Experiment results for *NetProfit* (average per-transaction profit) vs. $Cost(R_i)$ (reputation cost) are shown in Figure 4-19. Among the fixed-quantity selection approaches, selecting ten providers (s_{10}) achieves the highest average per-transaction *NetProfit* when reputation cost is zero, because purchasing reputation suggestions from more providers results in more accurate aggregate reputation-based suggestions, yet costs nothing. However, *NetProfit* from selecting ten providers quickly decreases as cost per reputation increases; for reputation costs greater than 0.24 per reputation, the cost of purchasing ten reputations outweighs transaction earnings, despite the accuracy of the aggregate reputation-based suggestion. In contrast, selecting only the single most accurate provider (s_1) yields the lowest per-transaction *NetProfit* when reputation cost is zero because the resulting aggregate suggestion is less accurate than when reputations from more providers are selected, and there is no cost savings by declining additional reputation providers. However, when reputation costs are high, selecting the single most accurate provider yields the highest average per-transaction *NetProfit* because reputation costs are minimized.

As Figure 4-19 shows, Adaptive Cost Selection selects the appropriate number of reputations from providers, depending on reputation cost and provider accuracy, for all reputation costs, achieving *NetProfit* statistically similar (α = 0.05) to that of the best fixed-quantity technique for the specific reputation cost. Figure 4-20 shows the similarity between the number providers chosen in the experiment by Adaptive Cost Selection and the theoretical computation for best number of providers, previously charted in Figure 4-13 (Section 4.1.4). When using Adaptive Cost Selection in the experiment, the truster always selects the scenario s_n with n lower than, but close to, the theoretical best n for which *MarginalReward* of the nth reputation equals $Cost(R_i)$, minimizing both aggregate suggestion error and total reputation cost. Due to randomness, the standard deviations of reputation provider suggestions are not all exactly 10; instead, they tend to fall within a range of approximately 9 to 11. As a result, *MarginalReward* for the first reputation purchased is higher than theoretically predicted (and *MarginalReward* for subsequent reputations is lower than theoretically predicted). Consequently, the empirical number of reputations selected (shown in Figure 4-20) is lower than the theoretically computed number to purchase.

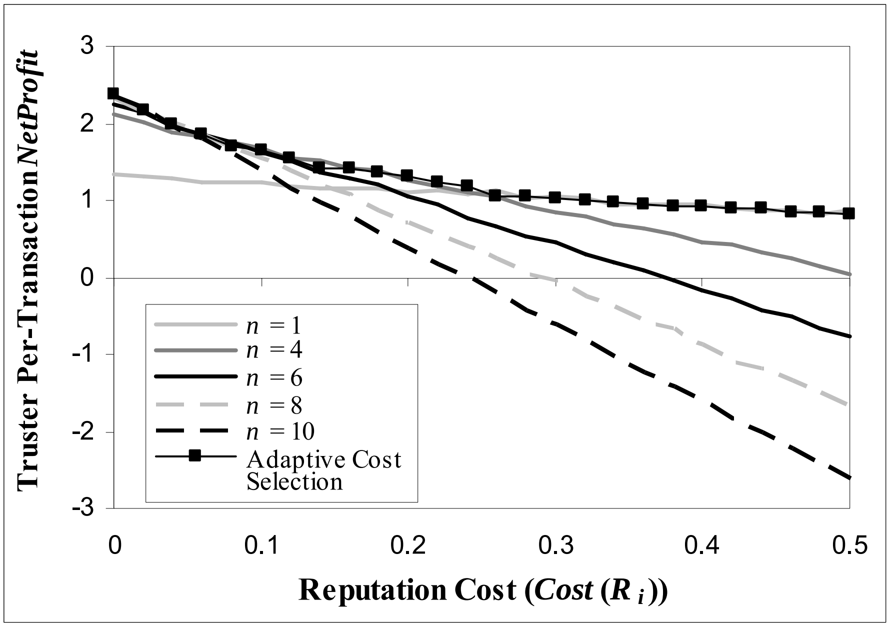


Figure 4-19. Truster's per-transaction *NetProfit* as a function of reputation cost (*Cost*(*R*$_i$)). Several approaches which each select a fixed number (*n*) of reputations to purchase are compared experimentally against Adaptive Cost Selection.

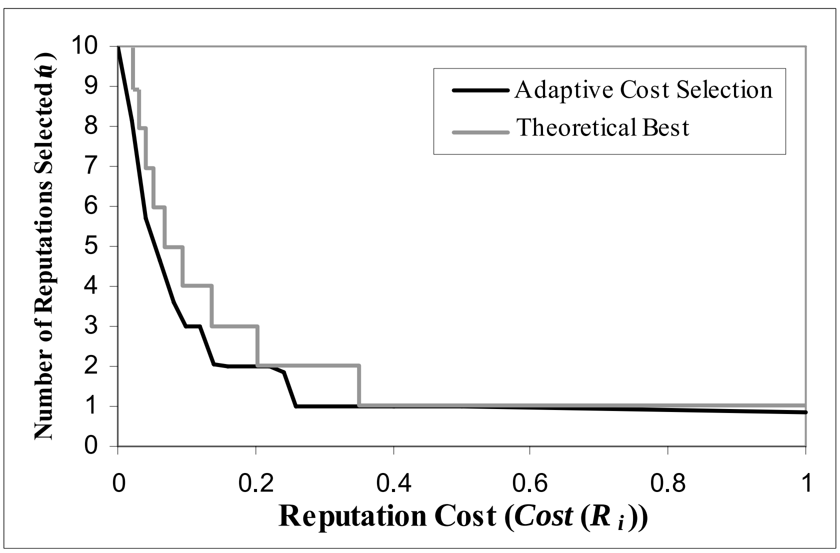


Figure 4-20. Number of selected reputations (*n*) as a function of reputation cost (*Cost*(*R*$_i$)). The number of reputation providers selected experimentally by the truster using Adaptive Cost Selection is compared against the theoretically-determined best *n* (as shown in Figure 4-13).

A second experiment is conducted in which the availability of experience-based trust information is accounted for in the Adaptive Cost Selection technique. This same experiment is references in Section 3.3.2, which demonstrates how a truster's reliance on its reputation-based trust model (ω_R) changes as the number of transaction observations (m) increases. This experiment validates the results in Section 3.3.2 by showing that Adaptive Cost Selection achieves *NetProfit* as high as, or higher than, the best fixed-quantity reputation selection technique for all reputation costs ($Cost(R_i)$) and number of transaction observations (m). In the experience-included case, the truster's experience-based model is viewed as an additional "reputation provider" whose suggestions have zero cost and error that decreases as the number of transaction observations (with the trustee in question) increases. Therefore, experience-based suggestions are always included in computing the aggregate suggestion. Scenario s_0 describes the scenario in which the suggestion from only the experience-based "provider" is included, while scenario s_1 includes the experience-based suggestion and the reputation from the single reputation provider with least error, and so on.

In addition to its experience-based model, a single truster has access to ten reputation providers, each providing reputation suggestions according to $N(\mu_{R,sug}, \sigma_{R,sug})$, where $\mu_{R,sug} = \mu_{beh}$ and $\sigma_{R,sug} = 10.0$. An experiment run consists of 100 transaction observations (m), during which the truster builds its experience-based trust model about a single trustee whose behavior P_{act} is normally distributed according to $N(\mu_{beh}, \sigma_{beh})$, where $\sigma_{beh} = 1.0$. The trustee's μ_{beh} is constant throughout a run, but over different runs, each with a different trustee, μ_{beh} is uniformly distributed between $P_{act,min} = -10.0$ and $P_{act,max} = 10.0$ (the truster's Adaptive Cost Selection technique uses the corresponding computation of *AverageReward* given by Equation 43 in Section 4.1.2, which assumes $P_{act,min} = -10.0$ and $P_{act,max} = 10.0$). Results from 9000 runs are averaged. The experiment compares the truster's average per-transaction profit (*NetProfit*, defined by Equation 48 in Section 4.1.4 as transaction earnings minus reputation costs) as a function of both reputation cost and number of observed transactions m (with the single trustee in question). The experiment results compare *NetProfit* achieved by Adaptive Cost Selection vs. always selecting a fixed quantity of the most accurate reputation providers: scenarios s_0 (experience-only), s_1, s_4, s_6, s_8, or s_{10}. In all cases, the truster includes, at no cost, suggestions from its experience-based model.

Figure 4-21 shows the truster's per-transaction *NetProfit* as a function of $Cost(R_i)$ when $m = 100$ (after 100 transactions with the trustee have been observed). As $Cost(R_i)$ increases, selecting zero reputations (s_0, using experience-based suggestions only), yields the highest *NetProfit*, while purchasing more reputations results in lower *NetProfit*. After 100 transaction observations, the truster's experience-based model is so accurate that reputation suggestions do not significantly improve the accuracy of the truster's aggregate suggestion, while paying for reputation suggestions only serves to decrease *NetProfit*. Adaptive Cost Selection achieves *NetProfit* statistically similar ($\alpha = 0.05$) to that of the best fixed-quantity case, selecting zero reputation providers and relying only on experience after enough transactions have been observed.

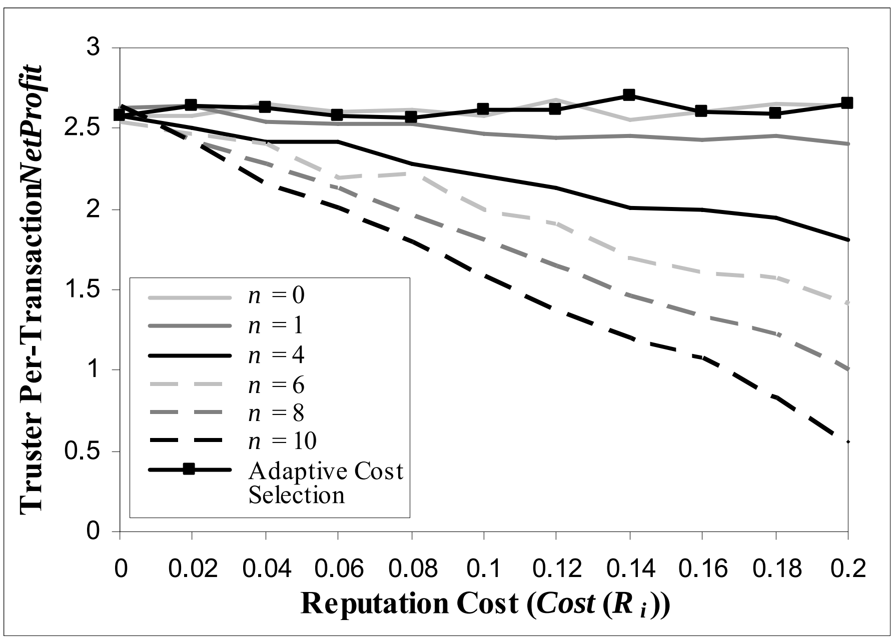


Figure 4-21. Truster's per-transaction *NetProfit* as a function of reputation cost (*Cost*(*R_i*)), when number of transaction observations (*m*) equals 100. Several approaches which each select a fixed number of reputations (*n*) to purchase are compared experimentally against Adaptive Cost Selection (in each case, the truster has access to experience-based suggestions).

Figure 4-22, Figure 4-23, and Figure 4-24 show the truster's per-transaction *NetProfit*, as the number of observed transactions (m) with the trustee increases, when $Cost(R_i)$ equals 0.2, 0.02, and 0.0, respectively (for visual clarity, only the fixed-quantity scenarios s_0, s_4, and s_{10} are shown, in addition to Adaptive Cost Selection). When

Cost(R_i) equals 0.2, reputation cost is too high to justify purchasing any reputations, even when *m* is small (the truster's experience-based model is not very accurate). As a result, purchasing fewer reputations results in highest *NetProfit*. When *Cost*(R_i) equals 0.02, s_{10} is advantageous when number of transaction observations (*m*) is low, because reputation cost is low and the truster's experience-based model has not yet built up sufficient accuracy. However, as the truster's experience-based model increases in accuracy (*m* increases), the contribution of each reputation to the truster's aggregate suggestion decreases, and the truster achieves higher *NetProfit* by relying on experience only (s_0). The Adaptive Cost Selection technique identifies the best number of reputations to purchase, given both reputation cost and experience-based model accuracy (based on *m*), decreasing the number of reputations purchased as *m* increases and the *MarginalReward* of each subsequent reputation decreases. When *Cost*(R_i) equals 0.0, the truster finds it advantageous to utilize as many reputations as possible—no matter how accurate its experience-based model—because purchased reputations incur no cost. Correspondingly, the fixed-quantity case of selecting ten reputations (s_{10}) yields the highest *NetProfit*, regardless of number of observed transactions. Adaptive Cost Selection matches the highest *NetProfit* by also purchasing ten reputations for all values of *m*. In all three figures, Adaptive Cost Selection achieves *NetProfit* statistically similar ($\alpha = 0.05$) to that of the fixed-quantity case yielding the highest *NetProfit* (purchasing zero and using experience only).

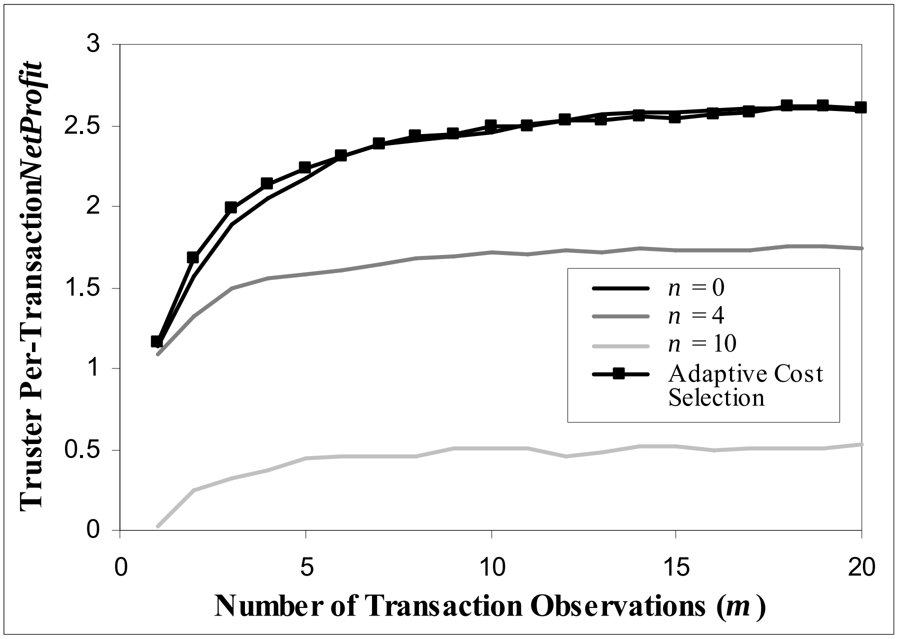


Figure 4-22. Truster's per-transaction *NetProfit* as a function of number of transaction observations (*m*), when reputation cost (*Cost*(R_i)) equals 0.2. Several approaches which each select a fixed number (*n*) of reputations to purchase are compared experimentally against Adaptive Cost Selection (in each case, the truster has access to experience-based suggestions).

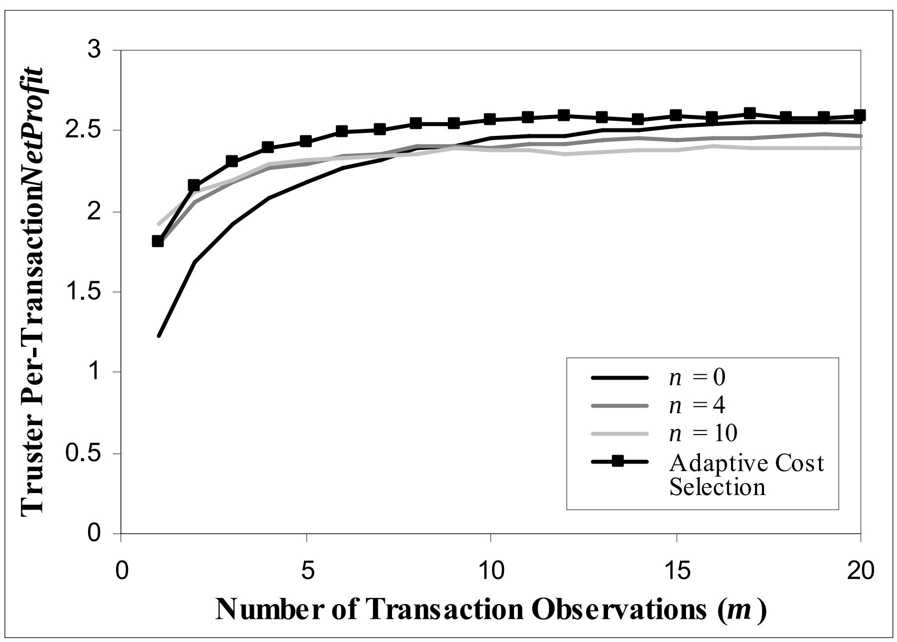


Figure 4-23. Truster's per-transaction *NetProfit* as a function of number of transaction observations (*m*), when reputation cost (*Cost*(R_i)) equals 0.02. Several approaches which each select a fixed number (*n*) of reputations to purchase are compared experimentally against Adaptive Cost Selection (in each case, the truster has access to experience-based suggestions).

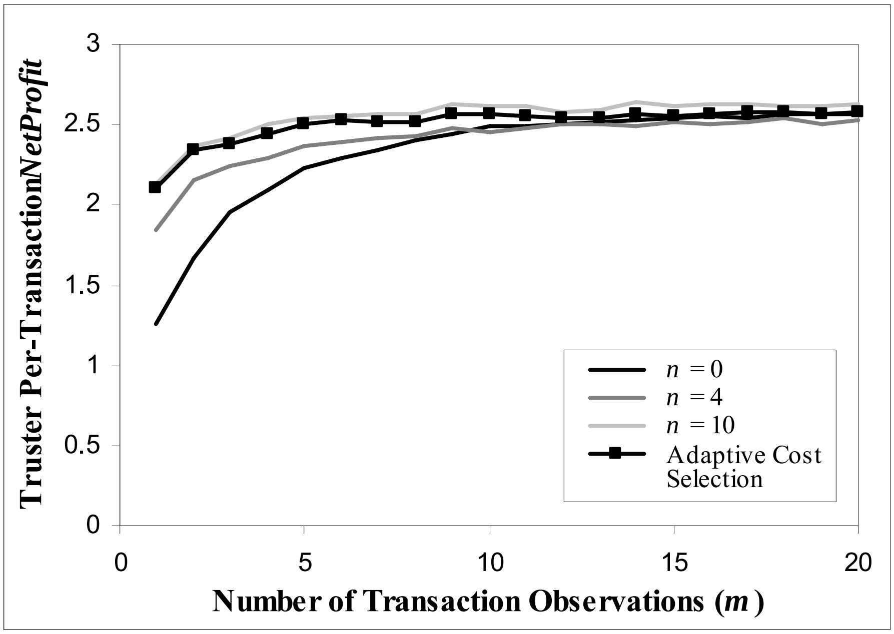


Figure 4-24. Truster's per-transaction *NetProfit* as a function of number of transaction observations (*m*), when reputation cost (*Cost*(R_i)) equals zero. Several approaches which each select a fixed number (*n*) of reputations to purchase are compared experimentally against Adaptive Cost Selection (in each case, the truster has access to experience-based suggestions).

Figure 4-25 compares the number of reputations purchased according to Adaptive Cost Selection as a function of reputation cost for three cases: 1) when $m = 3$ (before the truster's experience-based model achieves significant accuracy), 2) when $m = 100$ (after the truster's experience-based model has become very accurate), and 3) when no experience-based model is available (from Figure 4-20, for comparison purposes). Even when m is small, Adaptive Cost Selection purchases fewer reputations when the truster's experience-based model is available than when no experience-based model is available. When m is large (the truster's experience-based model is very accurate), even fewer reputations are purchased. Recall from Figure 3-41 in Section 3.3.2 that the truster's reliance on its aggregate reputation-based suggestion decreases as both m and $Cost(R_i)$ increase.

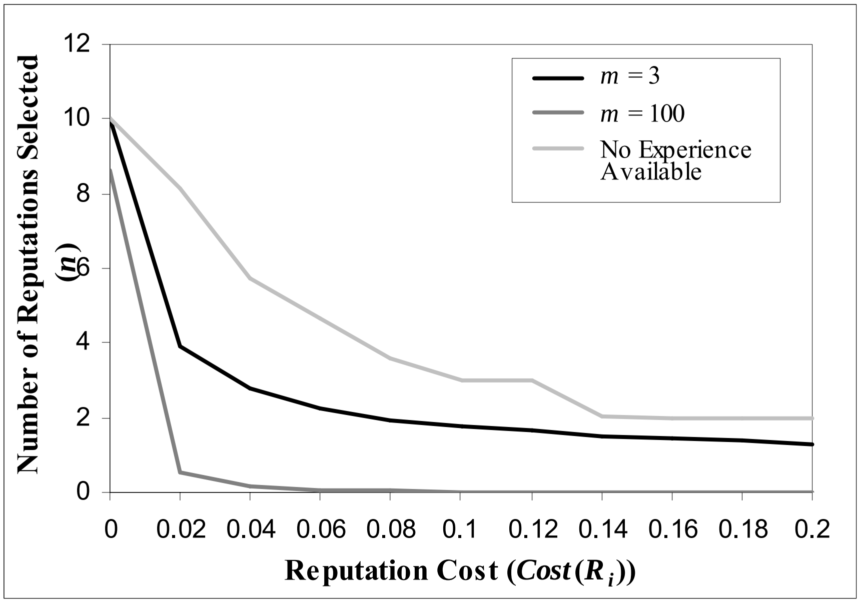


Figure 4-25. Number of reputations (*n*) selected as a function of reputation cost (*Cost*(*R_i*)). The number of reputations selected experimentally by the truster using Adaptive Cost Selection is compared when 1) *m* = 3, 2) *m* = 100, and 3) no experience-based model is available (as shown in Figure 4-20).

In summary, this research presents an adaptive technique for selecting reputation suggestions when reputation cost is a factor. Adaptive Cost Selection achieves *NetProfit* as high as the most profitable fixed-quantity reputation selection technique by weighing the cost of a reputation suggestion against the predicted accuracy of the reputation and resulting utility gained from it, in terms of payoff from the potential transaction. In general, when utilizing Adaptive Cost Selection, the truster selects reputations from more providers when reputation cost is low because the positive impact of increased suggestion accuracy on transaction payoff outweighs the negative impact of reputation cost. Conversely, when reputation cost is high, the truster selects reputations from fewer providers, though accuracy of the aggregated reputation-based suggestion suffers, because the negative impact of reputation cost outweighs the positive impact of increased accuracy otherwise. When suggestions from the truster's experience-based model are available, the truster selects more reputations early on, before the experience-based model has built up significant accuracy. However, as the truster's experience-based model gains accuracy, Adaptive Cost Selection purchases fewer reputations. The Adaptive Cost Selection technique assesses the *MarginalReward* of each reputation to find the optimal balance between reputation cost and increased aggregate suggestion accuracy.

4.2.2 CHOOSING APPROPRIATE *AVERAGEREWARD* FUNCTIONS

The experiments in Section 4.2.1, which demonstrate the advantage of Adaptive Cost Selection over strategies selecting fixed-quantities of reputations, assume the truster knows a priori that P_{act} over all trustees is distributed uniformly as $U[P_{act,min}, P_{act,max}]$, where $P_{act,min}$ = -10.0 and $P_{act,max}$ = 10.0. In those experiments, the truster uses the specific *AverageReward* function displayed in Figure 4-7, unique for the P_{act} distribution U[-10.0, 10.0], to compute the number of reputations to purchase given reputation cost $Cost(R_i)$. However, as detailed in Section 4.1.5, different distributions of P_{act} over trustees can yield very different *AverageReward* functions. Further, in many cases, a truster has no absolute knowledge about the distribution of P_{act} over trustees, outside of the individual transaction outcomes it observes. Therefore, an important step in justifying the usefulness of Adaptive Cost Selection requires removing the assumption that the distribution of P_{act} over trustees is known by the truster.

This section demonstrates how a truster can select the most appropriate *AverageReward* function given its estimate of the distribution of P_{act} over all potential trustees. The truster maintains an average, $\mu_{all,beh}$, and standard deviation, $\sigma_{all,beh}$, of transaction outcomes P_{act} over all trustees. For simplicity, the truster models the distribution of P_{act} over all trustees as uniform; therefore, $P_{act,min}$ and $P_{act,max}$ are computed from estimates of $\mu_{all,beh}$ and $\sigma_{all,beh}$:

$$P_{act,max} = \mu_{all,beh} + \sigma_{all,beh}\sqrt{3} \text{ and}$$
$$P_{act,min} = \mu_{all,beh} - \sigma_{all,beh}\sqrt{3} .$$

Before the truster has observed any transaction outcomes with any trustees, it assumes the distribution of P_{act} over all potential trustees is some default distribution (for the purpose of the experiments below, U[-1.0, 1.0] is used). As the truster observes transaction outcomes, it updates its estimates of $P_{act,min}$ and $P_{act,max}$ according to changes in $\mu_{all,beh}$ and $\sigma_{all,beh}$. The technique above enables a truster to dynamically select the most appropriate *AverageReward* function by estimating of the distribution of P_{act} over all potential trustees. The truster uses the *AverageReward* function to determine the scenario s_n (number n of error-ordered reputations to purchase) to maximize aggregate suggestion accuracy (and transaction payoff P_{act}) while minimizing reputation cost.

An experiment is conducted in which Adaptive Cost Selection (selecting the most appropriate *AverageReward* function based on estimates of the distribution of P_{act} over all potential trustees) is compared when the distribution of P_{act} is vs. is not known to the truster a priori. A single truster has access to ten reputation providers, each providing reputations according to $N(\mu_{R,sug}, \sigma_{R,sug})$, where $\mu_{R,sug} = P_{act}$ and $\sigma_{R,sug} = 10.0$, as in the first experiment of Section 4.2.1. The experiment averages 1,000 runs, each consisting of 100 transaction opportunities, each with a unique trustee. P_{act} values over all transaction opportunities are uniformly distributed between $P_{act,min} = -10.0$ and $P_{act,max} = 10.0$. For several values of reputation cost $Cost(R_i)$, the experiment compares 1) Adaptive Cost Selection assuming the distribution of P_{act} over all potential trustees is known to be U[-10, 10] against 2) Adaptive Cost Selection assuming the distribution of P_{act} over all potential trustees is unknown a priori, estimating the distribution of P_{act} over all potential trustees to select the most appropriate *AverageReward* function. Both Adaptive Cost Selection variations select scenario s_{10} as default during the first two transaction opportunities.

Figure 4-26, Figure 4-27, and Figure 4-28 show (a) number of reputations selected (n) and (b) *NetProfit* as functions of number of transaction opportunities (m) when $Cost(R_i)$ equals 0.0, 0.1, and 1.0, respectively. When $Cost(R_i)$ equals 0.0, Adaptive Cost Selection (with and without a priori knowledge of trustees' P_{act} distribution) automatically select scenario s_{10} (selecting all ten reputation providers), the scenario yielding the theoretically highest *NetProfit* (Figure 4-26a). *NetProfit* earned in the with vs. without a priori knowledge cases is statistically similar ($\alpha = 0.05$).

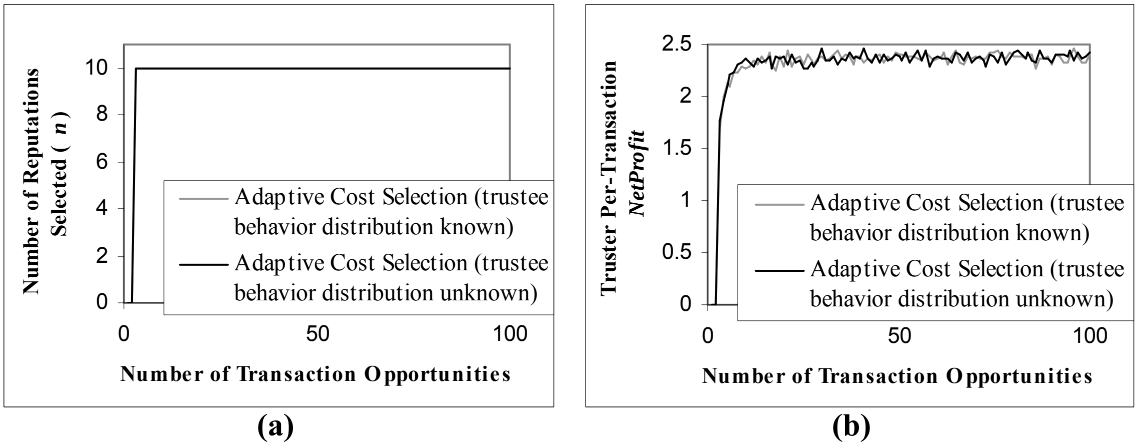
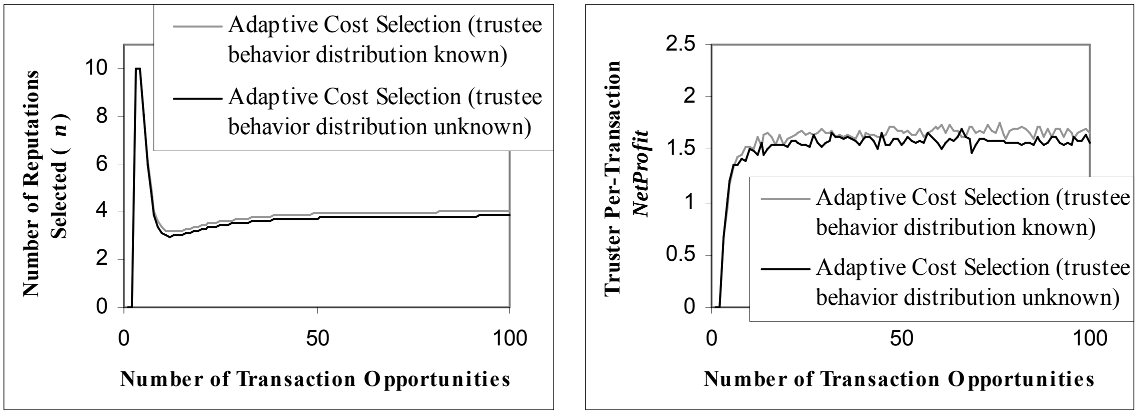


Figure 4-26. Adaptive Cost Selection compared when the distribution of P_{act} over all potential trustees is known vs. unknown in terms of (a) number of reputations in selected scenario s_n and (b) truster per-transaction *NetProfit* vs. number of transaction opportunities when $Cost(R_i)$ = 0.0.

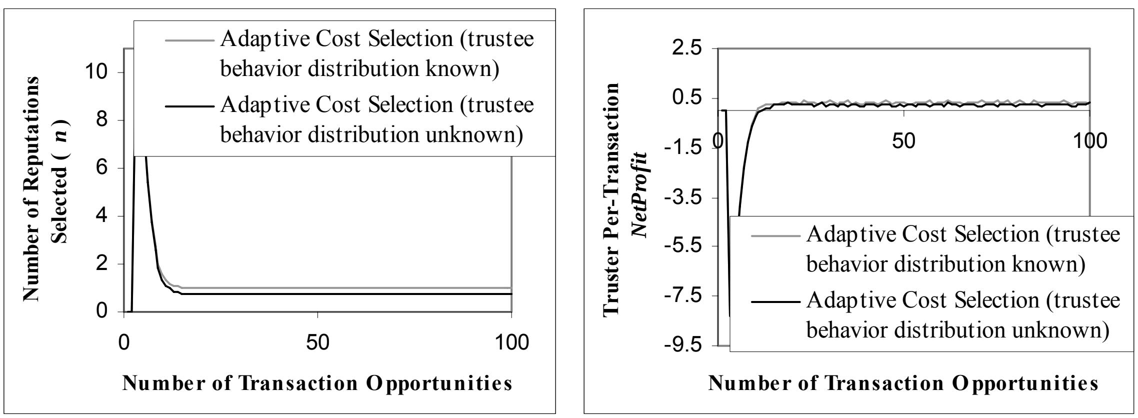
When $Cost(R_i)$ equals 0.1, Adaptive Cost Selection (with and without a priori knowledge of trustees' P_{act} distribution) quickly settles on selecting an average of about four reputations, once accurate estimates of reputation provider error are built up (Figure 4-27a). Adaptive Cost Selection without a priori knowledge selects slightly fewer reputations, on average; occasionally the algorithm is unable to form an accurate estimate of $P_{act,min}$ and $P_{act,max}$ because too many truster decisions result in not trusting, preventing the truster from observing instances of P_{act}. Adaptive Cost Selection without a priori knowledge achieves *NetProfit* values close to but significantly less than Adaptive Cost Selection with a priori knowledge (Figure 4-27b).

When $Cost(R_i)$ equals 1.0, Adaptive Cost Selection (with and without a priori knowledge of trustees' P_{act} distribution) quickly settles on selecting an average of about one reputation, once accurate estimates of reputation provider error are built up (Figure 4-28a). Again, Adaptive Cost Selection without a priori knowledge selects slightly fewer reputations, on average. Though both Adaptive Cost Selection versions initially yield negative *NetProfit* values, Adaptive Cost Selection quickly converges to yield a positive *NetProfit* (Figure 4-28b). Adaptive Cost Selection without a priori knowledge achieves *NetProfit* values close to but significantly less than Adaptive Cost Selection with a priori knowledge.



(a) **(b)**

Figure 4-27. Adaptive Cost Selection compared when the distribution of P_{act} over all potential trustees is known vs. unknown in terms of (a) number of reputations in selected scenario s_n and (b) truster per-transaction *NetProfit* vs. number of transaction opportunities when *Cost*(R_i) = 0.1.



(a) **(b)**

Figure 4-28. Adaptive Cost Selection compared when the distribution of P_{act} over all potential trustees is known vs. unknown in terms of (a) number of reputations in selected scenario s_n and (b) truster per-transaction *NetProfit* vs. number of transaction opportunities when *Cost*(R_i) = 1.0.

Figure 4-29 compares *NetProfit*, averaged over the first 100 transaction opportunities, as a function of *Cost*(R_i) for Adaptive Cost Selection with vs. without a priori knowledge of the P_{act} distribution. Removing the assumption that Adaptive Cost Selection has a priori knowledge of trustees' P_{act} distribution results in only a slightly significant (α = 0.05) decrease in average *NetProfit*.

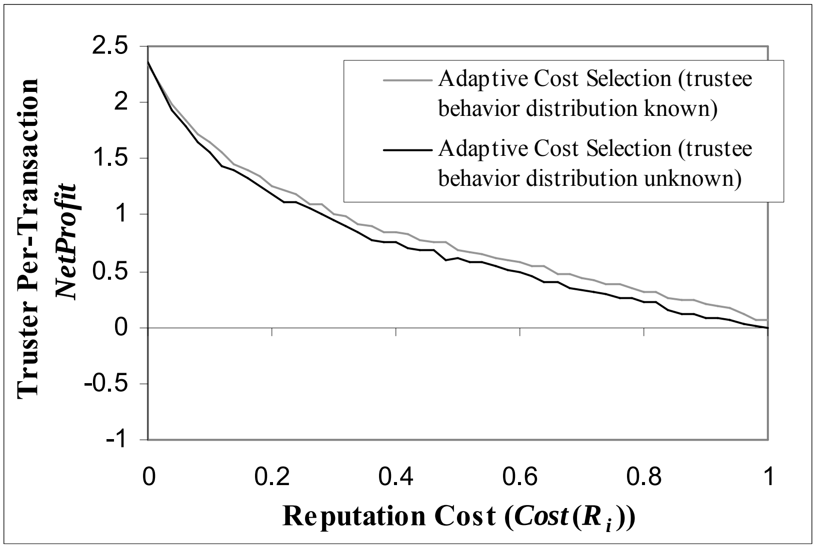


Figure 4-29. Adaptive Cost Selection compared when the distribution of P_{act} over all potential trustees is known vs. unknown in terms of truster per-transaction *NetProfit* vs. *Cost*(R_i).

In summary, it is not necessary to assume that Adaptive Cost Selection has a priori knowledge of the distribution of P_{act} over all potential trustees. Rather, even early (within approximately the first twenty transaction opportunities) estimates of the trustees' P_{act} distribution enable Adaptive Cost Selection to select an appropriate *AverageReward* function for selecting scenario s_n.

4.3 Applying Adaptive Cost Selection in the ART Testbed

This section explains experiments performed in the Agent Reputation and Trust (ART) Testbed demonstrating the effectiveness of Adaptive Cost Selection. The ART Testbed is an experimentation facility for trust-related research which provides an open-access platform for easily-repeatable experiments. Further, the ART Testbed provides a forum for competitions among agents designed by an international array of researchers. In the ART Testbed's art appraisal domain, agents function as appraisers, with varying levels of expertise, who earn fees by appraising paintings for clients. If an appraising agent does not have the expertise needed to complete the appraisal, it can choose to trust opinions it receives from other appraiser agents. Appraisers receive more clients, and thus more profit, for producing more accurate appraisals. In the experiments presented here, Adaptive Cost Selection is implemented as an improvement to the strategy of the

ART Testbed competition's winning agent. The experiments demonstrate that a winning-strategy agent implementing Adaptive Cost Selection earns higher net profits than a winning-strategy agent without Adaptive Cost Selection when the two agents compete against each other in the ART Testbed.

The ART Testbed Project began in 2004, when this author began recruiting an initial team of ten researchers from six countries to participate in software development and competition organization. The ART Testbed was conceived from the need to 1) attract researchers to interesting problems related to trust and reputation in multi-agent systems, 2) establish success benchmarks for trust-related technologies, and 3) provide a common experimentation platform enabling experiment repeatability. Version releases of the open source Testbed began in late 2005; ongoing improvements are initiated by the core development team, as well as other researchers and competitors who contribute new features and changes to existing code. International competitions were conducted in 2006 (involving 14 competitors from 7 research organizations) and 2007 (involving 18 competitors from 13 research organizations). As of this writing, 100 subscribers participate in the ART Testbed Project's discussion group [ART Testbed, 2007]. Further, numerous publications by researchers (most unaffiliated with the organizing team) have examined topics such as developing strategies for winning the competition [Kafali and Yolum, 2006; Teacy, et al., 2007], assessing the feasibility of coalition formation in the ART Testbed [Sen, et al., 2006], using the ART Testbed for trust algorithm experimentation [Fullam and Barber, 2006], and designing trust and reputation ontologies [Brandão, et al., 2007].

Experimentation demonstrating the contribution of Adaptive Cost Selection is performed within the ART Testbed facility for several reasons. First, the widespread involvement by the international agent trust research community in ART Testbed experimentation and competitions means solid benchmarks are established for assessing the contribution of new trust research. Specifically, the winning agents of the 2006 and 2007 ART Testbed competitions serve as comparison baselines for these experiments. Further, the experiments presented in this chapter are easily-repeatable, since the ART Testbed facility is open source and experiment parameters are explicitly defined.

Experimentation requires very little start-up effort; using the java programming language, the user builds an agent simply by coding nine methods—each regarding a different trust-related decision—inherited from an abstract agent class. Finally, the flexibility of the ART Testbed permits researchers to alter game rules and parameters in a straightforward manner, enabling the Adaptive Cost Selection algorithm implemented here to serve as a springboard for future experiments under different system conditions.

Section 4.3.1 explains the game rules in place for both the 2006 and 2007 competitions. Section 4.3.2 presents results [Fullam, et al., 2006] and an explanation of the winning strategy [Teacy, et al., 2007] for the 2006 competition. A listing of final scores for the 2007 competition, as well as a short explanation of differences between the 2006 and 2007 games, are included; however, 2007 competition details, including explanation of the winning agent strategy and in-depth analysis of results, are not yet available at the time of this writing. As a result, the discussion of Adaptive Cost Selection implementation in Section 4.3.3 is presented in the context of improving the 2006 winning agent. Winning agents of both the 2006 and 2007 competitions were designed by the same research team; that team has claimed, through informal communication, that changes between their 2006 and 2007 agents are insignificant. Therefore, experiments presented in Section 4.3.4 compare the earned profits of an agent utilizing Adaptive Cost Selection against the winning agents of both the 2006 and 2007 competitions.

4.3.1 THE ART TESTBED GAME RULES

This section provides a brief description of the ART Testbed game rules in effect for the 2006 and 2007 competitions. Additional details are provided in the official Testbed specifications and game rules publications [Fullam, et al., 2005a; Fullam, et al., 2005b; Fullam, et al., 2004]; updated rules associated with subsequent Testbed releases may be found at the ART Testbed website [ART Testbed, 2007]. In the ART Testbed game scenario, agents act as painting appraisers with varying levels of expertise in different artistic eras. Paying a fixed fee *f*, simulation-generated clients request appraisals for paintings from different eras. An appraising agent may generate its own valuation estimate (called an *opinion*) of the painting, or, if the appraising agent does not have the expertise to complete the appraisal, it may request opinions from other appraiser agents. Appraisers producing accurate appraisals receive more clients, and thus more fees, in future timesteps. The winning agent is the appraiser achieving the highest bank balance by the end of the game.

The ART Testbed defines an appraiser's expertise as its ability to generate an accurate opinion about the value of a painting, as described by a normal distribution of the error between the appraiser's opinion and the true painting value (known only by the simulation). The simulation creates opinions according to this error distribution, which has a mean of zero and a standard deviation s given by

$$s = \left(s^* + \frac{\alpha}{c_g} \right) t$$

where s^*, unique for each era, is an inverse measure of an appraiser's expertise in that era (the expertise is assigned to an appraiser by the simulation from a uniform distribution between 0.1 and 1.0, inclusive, in increments of 0.1). The value t is the true value of the painting to be appraised and α is a parameter, chosen by the competition organizers and fixed for all appraisers, relating opinion-generation cost to resulting opinion accuracy. An opinion provider chooses a variable cost c_g, representing time taken to examine the painting, to pay in generating an opinion about a painting's value (a higher c_g value results in increased opinion accuracy). By choosing to pay a higher cost, analogous to spending more time studying the painting, an opinion provider increases the accuracy of its opinion, which also depends on—and is ultimately limited by—the appraiser's expertise in the painting's era.

Appraisers may request opinions from as many other appraisers as desired for each painting, at a fixed cost c_p for each opinion transaction. An appraiser's final appraisal is computed as a weighted average of all requested opinions (including opinions generated by the appraiser itself); the appraiser selects weights for each opinion provider in correlation with its trust in each opinion provider. The Testbed simulation uses these weights to compute each final appraisal as a weighted average of the appraiser's requested opinions. After the simulation notifies the appraiser of the final appraisal and the painting's true value, an appraiser may use this feedback to revise its trust models of other opinion providers. Appraisers acting as opinion requesters must identify the most accurate opinion providers to produce accurate appraisals at low cost. Appraisers acting as opinion providers must determine the optimal amount c_g to minimize opinion-generation costs and prevent competitors from achieving highest appraisal accuracy, yet continue to profit from opinion requests from other appraisers.

For a fixed cost c_r, an appraiser may query another appraiser for reputations about an opinion provider. The reputation provider reports a reputation of the same form as weights submitted for final appraisal calculation; however, reputations need not be truthful. Appraisers acting as reputation requesters must identify those appraisers providing accurate reputations about honest opinion providers with high expertise, while minimizing reputation purchase costs. Appraisers acting as reputation providers must provide reputations which encourage requesters to continue purchasing recommendations while preventing competitors from obtaining accurate opinions.

Although clients are initially evenly distributed among appraisers, appraisers with more accurate final appraisals are rewarded with a larger share of the client base in subsequent timesteps (the total number of clients per timestep remains constant for the game duration). To calculate each appraiser's share of the client base, each appraiser a's average relative appraisal error, ε_a is first calculated:

$$\varepsilon_a = \frac{\sum_{c \in C_a} \frac{\left|p_c^* - t_c\right|}{t_c}}{\left|C_a\right|}$$

where C_a is the set of appraiser a's clients, p_c^* is appraiser a's final appraisal for client c, and t_c is the true value of the painting client c submitted to a for appraisal. Next, each appraiser a is assigned a preliminary client share $\tilde{r}_a$ according to its average relative appraisal error:

$$\tilde{r}_a = \left(\frac{\delta_a}{\sum_{b \in A} \delta_b} \right) \cdot \left|C\right| \qquad \text{Eqn 56}$$

where A is the set of all appraisers, C is the set of all clients, and

$$\delta_a := 1 - \frac{\varepsilon_a}{\sum_{b \in A} \varepsilon_b}. \qquad \text{Eqn 57}$$

Thus, the appraiser with the least average relative appraisal error achieves the highest preliminary client share. Finally, each appraiser *a*'s actual client share r_a is influenced by the appraiser's client share from the previous timestep:

$$r_a = q \cdot r_a^{'} + (1-q) \cdot \tilde{r}_a,$$

where $r_a^{'}$ is appraiser *a*'s client share in the previous timestep. The parameter *q*, a value between zero and one inclusive, reflects the influence of previous client share size on client share size in the next timestep.

Three changes from the 2006 competition are introduced for the 2007 competition. While the 2006 competition includes only five agents (competitors) per game, the 2007 competition adds fifteen “dummy” agents (five “cheating” agents, five “benevolent” agents, and five “neutral” agents) to each game, for a total of twenty agents per game. Second, the 2007 competition introduces mid-game, unexpected expertise changes. Finally, the software used for the 2007 competition (release version 1.0.4) includes updated features (improved data accessibility, faster running times) over the software used for the 2006 competition (release version 0.3.4), though these software improvements are irrelevant to agent strategies.

4.3.2 ART Testbed International Competitions

The 2006 ART Testbed international competition was conducted using the game parameters specified in Table 4-2. A final round of competition was conducted among the five highest-scoring participants in the preliminary round. Table 4-3 shows results from the final round, where average profit per timestep and normalized profit ratio are calculated as:

$$\text{average profit per timestep} = \frac{\text{average ending bank balance}}{\text{number of timesteps per game}} \text{ and}$$

$$\text{normalized profit ratio} = \frac{\text{average profit per timestep}}{f \cdot (\text{average number of clients per agent})}$$

Note that an in-depth analysis of the 2006 competition results is provided in [Fullam, et al., 2006]; more detailed game data, as well as .jar files for each participating agent (source code is not made public by competitors), are accessible via the ART Testbed website [ART Testbed, 2007].

Table 4-2. 2006 parameters

Game Parameter	Value
Average Number of Clients per Agent	20
Number of Timesteps per Game	60
Number of Competitors per Game	5
Opinion Accuracy Factor α	0.5
Previous Client Share Influence q	0.1
Client Fee f	100
Opinion Cost c_p	10
Reputation Cost c_r	1

Table 4-3. Rankings, by average profit per timestep, for the Final Round of the 2006 international competition.

Rank	Agent Name	Team Affiliation	Avg. Profit per Timestep	Normalized Profit Ratio
1	IAM	Univ. Southampton	2193	1.10
2	JOEY	Univ. Nebraska-Lincoln	1717	0.86
3	NEIL	Nanyang Technological Univ.	1710	0.86
4	FROST	Bogazici Univ.	1690	0.85
5	SABATINI	Univ. Carlos III de Madrid	1541	0.77

Average profit per timestep for a game determines a game's winning agent. Normalized profit ratio indicates profit irrespective of client fee f and overall client base size C (client base size is determined by number of competitors). Normalized profit ratio is useful for comparing results of the 2006 competition games against experimental games presented later in Section 4.3.4. The 2006 winning agent, IAM (designed by a University of Southampton team) achieves a normalized profit ratio of 1.10, as compared to the second-place agent, JOEY, which achieves a normalized profit ratio of 0.86. In other words, IAM maximizes its number of clients and earnings from selling opinions, while not paying too much to acquire opinions and generate opinions for other appraisers. Detailed data regarding client shares, opinion earnings, opinion-generation costs, and opinion purchase costs are contained in the 2006 competition analysis [Fullam, et al., 2006].

Game parameters for the 2007 ART Testbed competition are specified in Table 4-4 [ART Testbed, 2007]. Between the 2006 and 2007 competitions, the number of timesteps per game is increased from 60 to 200, and reputation cost c_r is decreased from 1.0 to 0.1. Table 4-5 shows results from the 2007 final round [ART Testbed, 2007] in terms of average profit per timestep, profit ratio, and normalized profit ratio. The winning agent, IAM2 (designed by the same University of Southampton team), achieves a normalized profit ratio of 2.77, as compared to the second-place agent, JAM, which achieves a normalized profit ratio of 1.86. Profit ratios are substantially higher in the 2007 competition, as compared to 2006, because the inclusion of fifteen dummy agents per game increases the total client base from 100 agents to 400. While dummy agents each retain some small client share, the majority of clients are acquired by the more accurate-appraising competitor agents.

Interestingly, in all but rare instances, participants in both the 2006 and 2007 competitions make no use of reputation exchange [Fullam, et al., 2006; ART Testbed, 2007] (Section 4.3.5 explores the reasons and makes suggestions for game rule changes to encourage reputation exchange). Therefore, applying Adaptive Cost Selection to reputation purchasing decisions provides little benefit, given the described ART Testbed competition game setup. However, appraisers make similar decisions regarding opinion purchases, weighing the cost to acquire opinions against the increased accuracy of appraisals (and increased client earnings). IAM's policies regarding purchasing and weighting opinions, as part of its larger strategy, are described here as the baseline for the implementation of Adaptive Cost Selection presented in Section 4.3.3. IAM (2006) (as opposed to IAM2 (2007)) is studied, since 1) detailed documentation about the IAM strategy exists and 2) the Southampton designers informally suggest that changes between IAM and IAM2 are insignificant. Nevertheless, experiments are conducted using both IAM and IAM2 agents in Section 4.3.4.

Table 4-4. 2007 Parameters

Game Parameter	Value
Average Number of Clients per Agent	20
Number of Timesteps per Game	200
Number of Competitors per Game	5
Opinion Accuracy Factor α	0.5
Previous Client Share Influence q	0.1
Client Fee f	100
Opinion Cost c_p	10
Reputation Cost c_r	0.1

Table 4-5. Rankings, by average profit per timestep, for the Final Round of the 2007 international competition.

Rank	Agent Name	Team Affiliation	Avg. Profit per Timestep	Normalized Profit Ratio
1	IAM2	Univ. Southampton	5536	2.77
2	JAM	Univ. Tulsa	3715	1.86
3	BLIZZARD	Bogazici Univ.	3620	1.81
4	SPARTAN	Univ. Girona	3374	1.69
5	ZECARIOCALES	Univ. Rio de Janeiro	2893	1.45

The following summary gives an overview of the IAM strategy for purchasing opinions. IAM strategy elements are explained in greater detail in [Teacy, et al., 2007]. The IAM agent purchases opinions from providers in order of least to greatest error variance ($\sigma^2_{OP_i}$), acquiring each additional opinion if adding the opinion decreases the cumulative expected variance by at least 15%. The 15% error variance improvement threshold is empirically determined according to the given competition parameters in Table 4-2 (as demonstrated in Section 4.3.3, the optimal threshold for adding an additional opinion is dependent on opinion cost, c_p, and client fee, f). In similar fashion to the technique discussed in Ch 5.1.3 for selecting reputation providers, the IAM agent determined weights for each provider's opinion according to inverse variance,

$$\omega_i = \frac{\frac{1}{\sigma_{OP_i}^2}}{\sum_{j=1}^{n}\left(\frac{1}{\sigma_{OP_j}^2}\right)}.$$

IAM's 15% error variance improvement threshold does not account for variations in opinion cost and client fee (justifiably so, since these parameters are fixed in the competition setting). Section 4.3.3 describes how Adaptive Cost Selection, when implemented in place of the 15% variance improvement threshold, allows an agent to achieve net profits higher than those of an IAM agent, over a wide range of opinion costs and client fees, when the two agents compete against each other in the ART Testbed.

4.3.3 IMPLEMENTING ADAPTIVE COST SELECTION IN THE ART TESTBED

This section describes the implementation of Adaptive Cost Selection in an agent here called ACS-Agent. ACS-Agent is based on the IAM strategy [Teacy, et al., 2007] (here called "IAM-Agent"), but replaces the 15% error variance improvement threshold with the Adaptive Cost Selection technique for purchasing opinions in all opinion cost and client fee situations. The calculations presented here assume a single ACS-Agent competes against a single IAM-Agent.

As does IAM-Agent, ACS-Agent relies on statistical estimates of each opinion provider OP_i's error (standard deviations, σ_{OP_i}). Until providers' error standard deviations can be estimated (i.e. during the first two timesteps, t_1 and t_2), ACS-Agent selects a small number of opinions for each client's painting: at least one opinion, but as many opinions n_{ACS} as can be purchased by using ten percent of the client fee earned by that painting:

$$n_{ACS}(t_1) = n_{ACS}(t_2) = \max\left(\text{floor}\left(\frac{0.1 \cdot f}{c_p}\right), 1\right).$$

From the list of error standard deviations it maintains, ACS-Agent estimates the number of opinions per client, n_{IAM}, an opponent IAM-Agent will purchase (from opinion providers with least to greatest error standard deviation, based on the 15% error variance improvement threshold) and the error standard deviation, σ_{IAM}, of the IAM-Agent's aggregate appraisal., where

$$\sigma_{IAM} = \frac{\sqrt{\sum_{i=1}^{n_{IAM}} \sigma_{OP_i}^2}}{n_{IAM}}.$$

Based on its estimate of σ_{IAM}, ACS-Agent estimates the client shares of both itself and IAM-Agent (r_{ACS} and r_{IAM}, respectively), in terms of its own potential aggregate appraisal error, σ_{ACS} (which is undetermined at this point). From Equation 57 in Section 4.3.1:

$$\delta_a := 1 - \frac{\varepsilon_a}{\sum_{b \in A} \varepsilon_b}.$$

Assuming the entire client case C is divided among one ACS-Agent and one IAM-Agent only,

$$\delta_{ACS} = 1 - \frac{\varepsilon_{ACS}}{\varepsilon_{IAM} + \varepsilon_{ACS}}$$

$$\delta_{ACS} = \frac{\varepsilon_{IAM}}{\varepsilon_{IAM} + \varepsilon_{ACS}}.$$

From Equation 56 in Section 4.3.1 an agent a's preliminary client share is computed as:

$$\tilde{r}_a = \left(\frac{\delta_a}{\sum_{b \in A} \delta_b} \right) \cdot |C|.$$

Therefore,

$$\tilde{r}_{ACS} = \left(\frac{\delta_{ACS}}{\delta_{IAM} + \delta_{ACS}} \right) C$$

$$\tilde{r}_{ACS} = \left(\frac{\dfrac{\varepsilon_{IAM}}{\varepsilon_{IAM} + \varepsilon_{ACS}}}{\dfrac{\varepsilon_{ACS}}{\varepsilon_{IAM} + \varepsilon_{ACS}} + \dfrac{\varepsilon_{IAM}}{\varepsilon_{IAM} + \varepsilon_{ACS}}} \right) C$$

$$\tilde{r}_{ACS} = \left(\frac{\varepsilon_{IAM}}{\varepsilon_{ACS} + \varepsilon_{IAM}} \right) C.$$

From Equation 29 in Section 3.2.1,

$$\varepsilon = \sigma\sqrt{\frac{2}{\pi}}\,.$$

Therefore,

$$\tilde{r}_{ACS} = \left(\frac{\sigma_{IAM}\sqrt{\frac{2}{\pi}}}{\sigma_{ACS}\sqrt{\frac{2}{\pi}} + \sigma_{IAM}\sqrt{\frac{2}{\pi}}}\right)C$$

$$\tilde{r}_{ACS} = \left(\frac{\sigma_{IAM}}{\sigma_{ACS} + \sigma_{IAM}}\right)C\,.$$

If equilibrium is assumed, then an agent's previous share ($r_a^{'}$) equals its current share ($\tilde{r}_a$), so $r_a = \tilde{r}_a$ for all q. As a result,

$$r_{ACS} = \left(\frac{\sigma_{IAM}}{\sigma_{ACS} + \sigma_{IAM}}\right)C\,. \qquad \text{Eqn 58}$$

Further,

$$r_{IAM} = \left(\frac{\sigma_{ACS}}{\sigma_{ACS} + \sigma_{IAM}}\right)C\,. \qquad \text{Eqn 59}$$

Both agents' *NetProfit* (earnings from client fees minus total opinion costs),

$$NetProfit_{ACS} = r_{ACS}\left(f - n_{ACS}c_p\right) \text{ and}$$

$$NetProfit_{IAM} = r_{IAM}\left(f - n_{IAM}c_p\right),$$

are estimated in terms of ACS-Agent's potential aggregate appraisal error, σ_{ACS} (substituting Equation 58 and Equation 59):

$$NetProfit_{ACS} = \left(\frac{\sigma_{IAM}}{\sigma_{ACS} + \sigma_{IAM}}\right)C\cdot\left(f - n_{ACS}c_p\right) \text{ and} \qquad \text{Eqn 60}$$

$$NetProfit_{IAM} = \left(\frac{\sigma_{ACS}}{\sigma_{ACS} + \sigma_{IAM}}\right)C\cdot\left(f - n_{IAM}c_p\right).$$

If ACS-Agent's goal were to maximize its *NetProfit*, it could simply build a scenario table (as described in Section 4.1.3) in which *AverageReward* and *MarginalReward* are computed for each possible value of n_{ACS}, where

$$AverageReward_{ACS} = \left(\frac{\sigma_{IAM}}{\sigma_{ACS} + \sigma_{IAM}} \right) C \cdot f \text{ and}$$

$$MarginalReward_{ACS}\left(n_{ACS}\right) = AverageReward_{ACS}\left(n_{ACS}\right) - AverageReward_{ACS}\left(n_{ACS} - 1\right)$$

Figure 4-30 shows *MarginalReward* of a provider's opinions (yielded over all clients) as a function of opinion provider ranking i_{ACS}, for an example case in which ACS-Agent has a choice between ten opinion providers, σ_{OP_i} = 0.5 for all providers, C = 200, and f = 100. Unlike the situation in Section 4.1.4, in which cost ($Cost(R_i)$) is constant for each additional reputation purchased (R_i), in the ART Testbed, cost (here called *MarginalCost*) increases as ranking n_{ACS} increases, since ACS-Agent must purchase an additional opinion for *each* new client it acquires. AverageCost, the total opinion costs for a given timestep, is computed as:

$$AverageCost_{ACS} = \left(\frac{\sigma_{IAM}}{\sigma_{ACS} + \sigma_{IAM}} \right) C \cdot \left(n_{ACS} c_p \right)$$

Further,

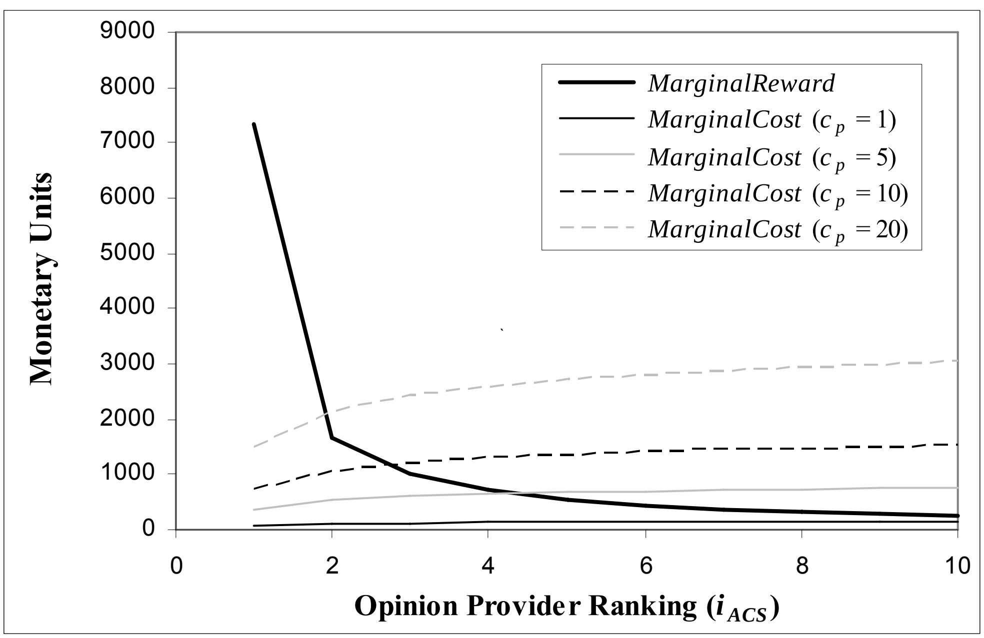


Figure 4-30. *MarginalReward* and *MarginalCost* (c_p = 1, 5, 10, 20) as functions of opinion provider ranking, i_{ACS} (σ_{OP_i} = 0.5 for ten providers, C = 200, and f = 100).

$$MarginalCost_{ACS}\left(n_{ACS}\right) = AverageCost_{ACS}\left(n_{ACS}\right) - AverageCost_{ACS}\left(n_{ACS} - 1\right)$$

In Figure 4-30, *MarginalCost* is shown for example cases in which c_p equals 1, 5, 10, and 20. Figure 4-31 shows $NetProfit_{ACS}$ (Equation 60) for the c_p = 5 case; ACS-Agent's *NetProfit* is maximized when *MarginalCost* = *MarginalReward* at n_{ACS} = 4. However, in some cases, selecting the highest $NetProfit_{ACS}$ also results in a high $NetProfit_{IAM}$. Instead, ACS-Agent must seek to maximize its *NetProfit* advantage (adv_{ACS}), where

$$adv_{ACS} = NetProfit_{ACS} - NetProfit_{IAM}$$

$$adv_{ACS} = \left[\left(\frac{\sigma_{IAM}}{\sigma_{ACS} + \sigma_{IAM}}\right)C \cdot \left(f - n_{ACS}c_p\right)\right] - \left[\left(\frac{\sigma_{ACS}}{\sigma_{ACS} + \sigma_{IAM}}\right)C \cdot \left(f - n_{IAM}c_p\right)\right]$$

$$adv_{ACS} = \frac{C}{\sigma_{ACS} + \sigma_{IAM}}\left[\sigma_{IAM}\left(f - n_{ACS}c_p\right) - \sigma_{ACS}\left(f - n_{IAM}c_p\right)\right].$$

In the equation for adv_{ACS} above, all values are known (C, f, and c_p) or estimated (n_{IAM} and σ_{IAM}), except for ACS-Agent's number of opinions per client to purchase (n_{ACS}) and resulting aggregate appraisal error (σ_{ACS}). To determine the number of opinions per client to purchase (n_{ACS}) to maximize adv_{ACS}, ACS-Agent builds a scenario table, computing adv_{ACS} for each scenario s_n. A scenario s_n describes the resulting aggregate appraisal error (σ_{ACS}) and *NetProfit* advantage (adv_{ACS}) ACS-Agent achieves from purchasing opinions from providers 1 through n for each client (when providers are ordered from least to greatest provider error, σ_{OP_i}). Figure 4-32 shows $NetProfit_{ACS}$ and $NetProfit_{IAM}$ as functions of n_{ACS} (for the same case in which c_p = 5 and σ_{OP_i} = 0.5 for all providers). $NetProfit_{IAM}$ decreases as n_{ACS} increases since ACS-Agent's appraisal accuracy increases with more opinions, taking client share away from IAM-Agent. Figure 4-32 also shows adv_{ACS}; in the example case, adv_{ACS} is maximized when n_{ACS} equals 6.

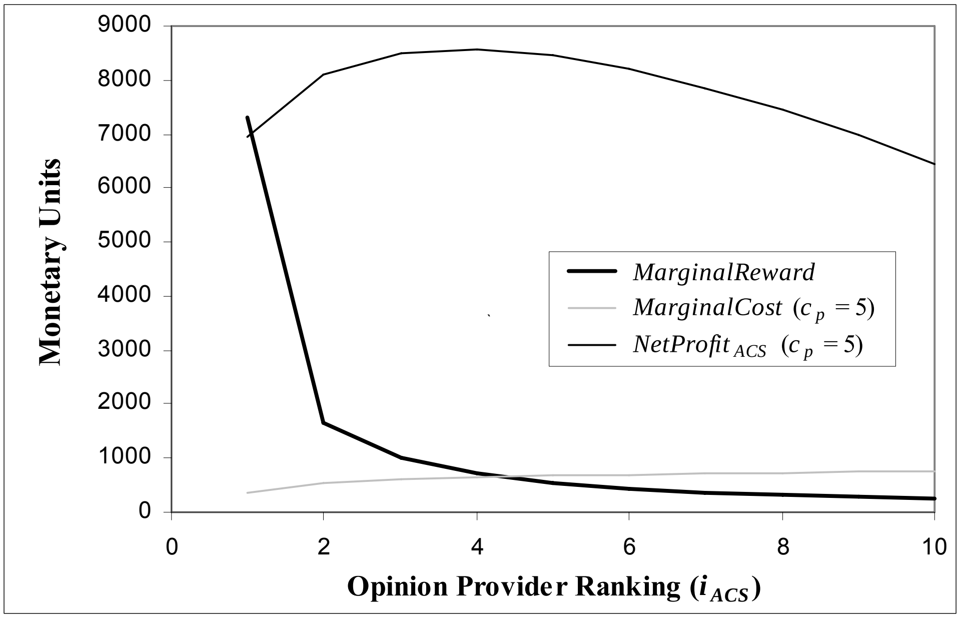


Figure 4-31. ***MarginalReward*, *MarginalCost*, and resulting *NetProfit*$_{ACS}$ as functions of opinion provider ranking, i_{ACS} (σ_{OP_i} = 0.5 for ten providers, C = 200, f = 100, and c_p = 5). Maximum *NetProfit*$_{ACS}$ is achieved when ACS-Agent purchases opinions the four providers with lowest expected error (n_{ACS} = 4).**

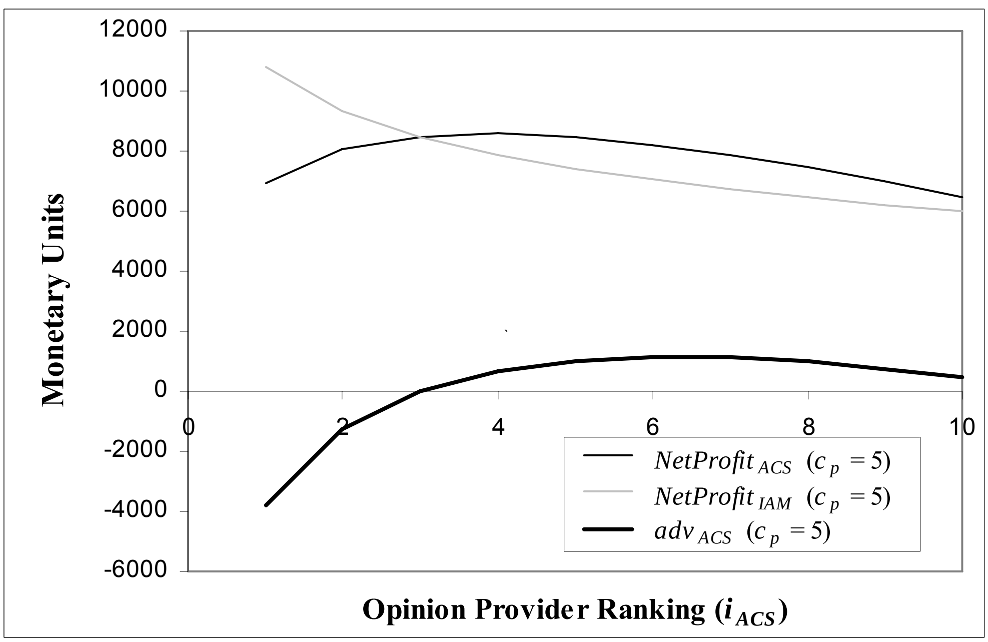


Figure 4-32. ***NetProfit*$_{ACS}$, *NetProfit*$_{IAM}$, and resulting *adv*$_{ACS}$ as functions of number of opinions purchased per client, n_{ACS} (σ_{OP_i} = 0.5 for ten providers, C = 200, and f = 100, and c_p = 5). Maximum *adv*$_{ACS}$ is achieved when ACS-Agent purchases (for each client) opinions from the six providers with lowest expected error.**

4.3.4 Experimental Setup and Results

These experiments demonstrate that applying Adaptive Cost Selection to IAM's strategy enables an agent to achieve higher profits, when competing against an IAM agent that is not equipped with Adaptive Cost Selection, across a range of values for opinion cost (c_p) and client fees (f). In the competition version of the ART Testbed game rules, confounding factors (such as an appraiser's strategy for generating and selling opinions) influence net profit earnings. Therefore, for the purpose of these experiments, limitations are placed on roles each type of agent plays. Each game consists of one ACS-Agent, one IAM-Agent, and ten "opinion provider" agents, which behave as follows:

ACS-Agent: The ACS-Agent acts as an appraiser agent, executing the algorithm described in Section 4.3.3 (implementing Adaptive Cost Selection) with regard to opinion requesting and weighting. All appraiser agents, including the ACS-Agent, may only requests opinions from opinion provider agents. The ACS-Agent does not make opinion-providing decisions, since neither appraiser agents nor opinion provider agents request opinions from appraiser agents. Reputation-exchange is deactivated system-wide; therefore, ACS-Agents (and all other agents) make no decisions about requesting or providing reputations.

IAM-Agent: The IAM-Agent acts as an appraiser agent, executing IAM's strategy, as described in Section 4.3.2 (implementing the 15% error variance improvement threshold) with regard to opinion requesting and weighting. In all other respects, the IAM-Agent behaves similarly to the ACS-Agent.

Opinion Provider Agent: Opinion provider agents are assigned expertise values (s^*) which remain constant throughout a game. Opinion providers are not considered competitors in these experiments. Opinion providers do not act as appraisers for clients; therefore, they do not request nor weight opinions, nor do they earn client fees. When an ACS-Agent or IAM-Agent requests an opinion, the opinion provider agent invests an amount c_g, which is the same for every opinion generated.

Experiment parameters are listed in Table 4-6 for Experiment 1 (c_g = 10) and Experiment 2 ($c_g = c_p$). Parameter settings α and q are identical to competition settings. Each game is run for 100 timesteps, and the average number of clients per agent is 100 (since opinion providers are not considered competitors, the total number of clients is 200). Results are averaged from twenty games for each combination of opinion cost c_p (0 to 24) and client fee f (50, 100, 200, or 500), where c_p and f are constant throughout a game.

Table 4-6. Parameters for Experiment 1 (opinion providers invest c_g = 10 units when generating opinions) and Experiment 2 (opinion providers invest c_g = c_p).

Game Parameter	Value
Average Number of Clients per Agent	100
Number of Timesteps per Game	100
Number of Competitors per Game	2
Number of Opinion Providers per Game	10
Opinion Accuracy Factor α	0.5
Previous Client Share Influence q	0.1
Client Fee f	50 to 500
Opinion Cost c_p	0 to 24
Reputation Cost c_r	N/A
Opinion Provider Investment in Opinion c_g	10 or c_p

Results for Experiment 1 (in which c_g = 10) show per-timestep *NetProfit* for both ACS-Agent and IAM-Agent as a function of opinion cost c_p (Figure 4-33 (charts a-d) assumes client fee f equals 50, 100, 200, and 500, respectively). For all values of f and c_p, ACS-Agent earns *NetProfit* that is equal to or higher than its opponent, IAM-Agent. When f = 100 and c_p = 10 (Figure 4-33b), ACS-Agent and IAM-Agent achieve the same *NetProfit*; since IAM-Agent's 15% error variance improvement threshold is customized to those values of f and c_p (competition settings). The 15% threshold appears to generate highest possible *NetProfit* in cases where c_p/f = 0.1 (as shown by f = 50 and c_p = 5 in Figure 4-33a, and f = 200 and c_p = 20 in Figure 4-33c). Specifically, *NetProfits* for ACS-Agent and IAM-Agent are statistically similar (α = 0.05) when c_p = 4 for f = 50, c_p = 6, 8, 12, and 18 for f = 100, and c_p = 12 to 24 for f = 200. The difference between ACS-Agent's profit and IAM-Agent's profit is greatest when c_p is much greater or less than 0.1f. When opinion costs are very low compared to client fees, ACS-Agent takes advantage of the opportunity to buy many opinions per client, giving it a slightly lower appraisal error rate (and higher client share) than IAM-Agent, with only slightly higher total opinion costs. When opinion costs are very high, ACS-Agent sacrifices appraisal accuracy (resulting in a smaller client share) to avoid total opinion costs that would outweigh the benefit of more clients.

Figure 4-34 displays results for Experiment 2, in which $c_g = c_p$ (Figure 4-34, charts a-d, assume f equals 50, 100, 200, and 500, respectively). Experiment 2 results are very similar to those of Experiment 1, demonstrating that the amount opinion providers invest in opinions does not affect whether ACS-Agent earns higher profits than IAM-Agent. In Experiment 2, ACS-Agent earns *NetProfit* that is equal to or higher than its opponent, IAM-Agent for all values of f and c_p. Specifically, *NetProfits* for ACS-Agent and IAM-Agent are statistically similar ($\alpha = 0.05$) only when $c_p = 4$ for $f = 50$. Lastly, Figure 4-35 displays results showing ACS-Agent competing against the 2007 winning agent, IAM2-Agent, under Experiment 1 conditions, in which $c_g = c_p$ (Figure 4-35, charts a-d, assume f equals 50, 100, 200, and 500, respectively). For all values of f and c_p, ACS-Agent earns *NetProfit* that is (statistically) significantly higher than its opponent, IAM2-Agent. In many cases, the difference between ACS-Agent's profit and IAM2-Agent's profit is greater than when ACS-Agent competes against IAM-Agent. Unfortunately, IAM2-Agent's exact strategy has not yet been released to the public, so it is difficult to ascertain the reason for the difference in outcomes when ACS-Agent's competes against IAM-Agent vs. IAM2-Agent.

In summary, Adaptive Cost Selection enables the winning agent, in the ART Testbed competition, IAM, to better assess the utility of acquiring opinions, based on the cost of those opinions and the expected increase in appraisal accuracy (and thus, increase in client earnings). Adaptive Cost Selection provides the highest improvement in *NetProfit* when c_p/f is much greater or lower than 0.1, the ratio to which IAM is optimized for competition settings.

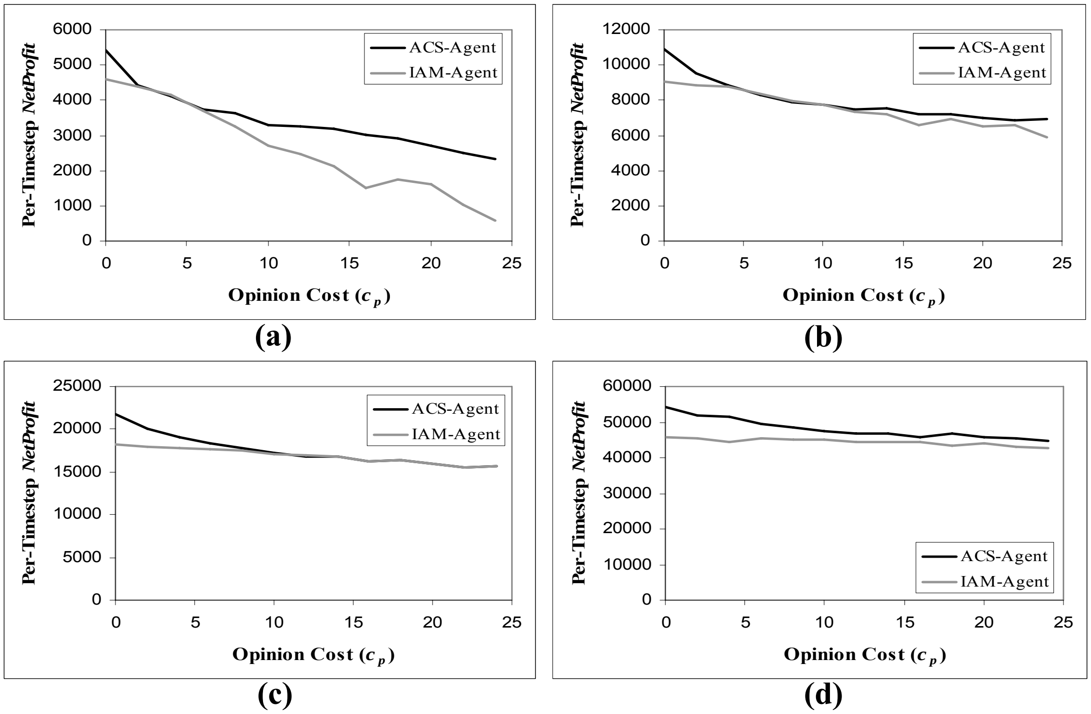


Figure 4-33. Per-timestep *NetProfit* for ACS-Agent and IAM-Agent as functions of opinion cost, c_p, when client fee, *f*, equals (a) 50, (b) 100, (c) 200, and (d) 500. Opinion providers invest 10 units in generating each opinion.

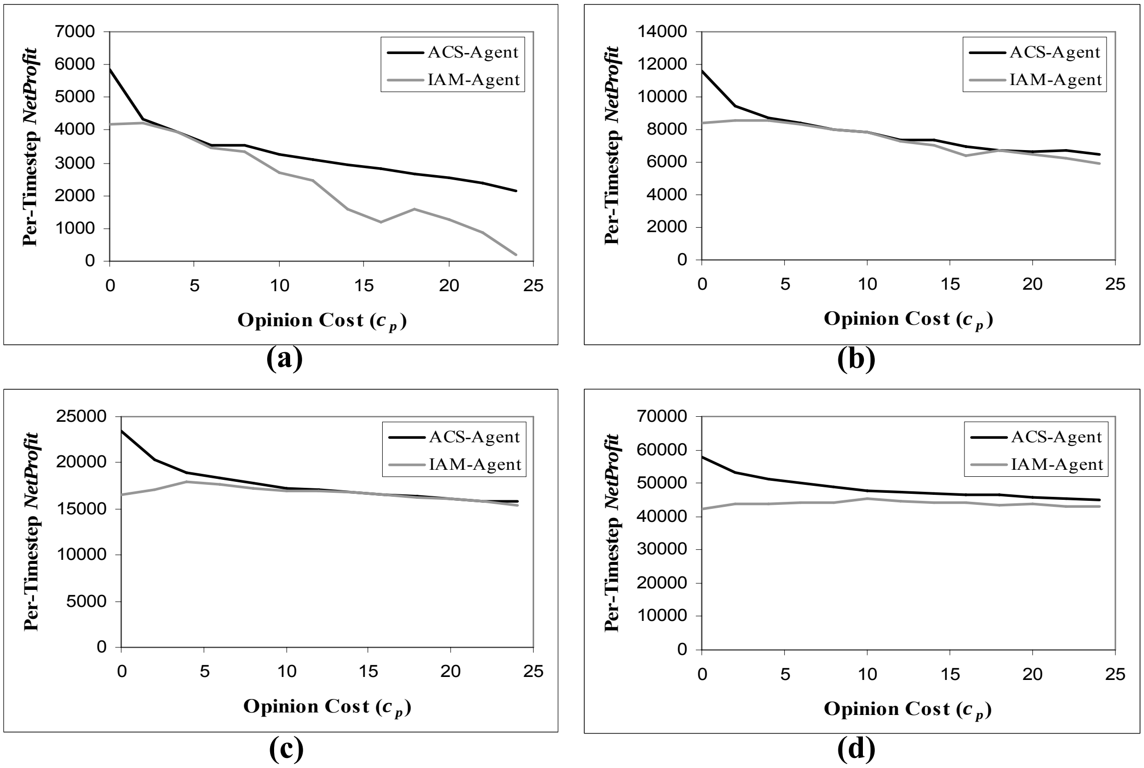


Figure 4-34. Per-timestep *NetProfit* for ACS-Agent and IAM-Agent as functions of opinion cost, c_p, when client fee, *f*, equals (a) 50, (b) 100, (c) 200, and (d) 500. Opinion providers invest c_p units in generating each opinion.

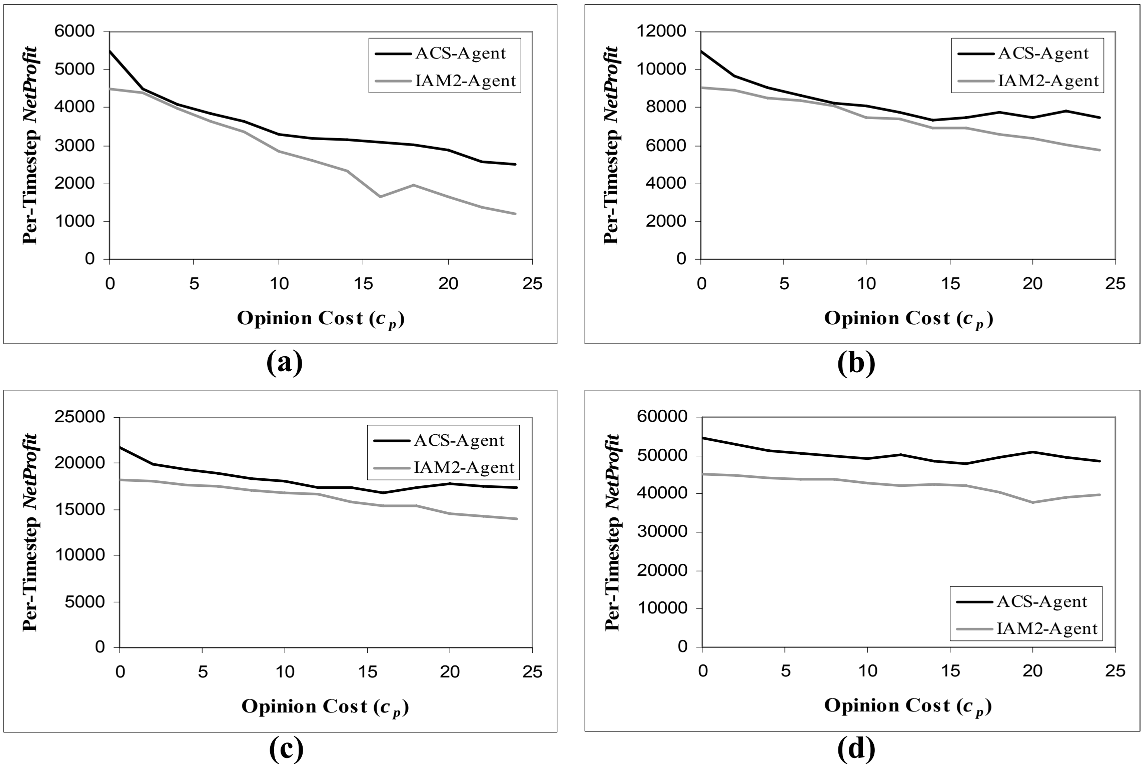


Figure 4-35. Per-timestep *NetProfit* for ACS-Agent and IAM2-Agent as functions of opinion cost, c_p, when client fee, *f*, equals (a) 50, (b) 100, (c) 200, and (d) 500. Opinion providers invest 10 units in generating each opinion.

4.3.5 ENCOURAGING REPUTATION EXCHANGE IN THE ART TESTBED

This side discussion applies the quantitative analysis of when reputation-based trust modeling is most useful (discussion in Chapter 3) to the problem of encouraging reputation exchange in the ART Testbed. As stated in Section 4.3.2, successful appraiser strategies in the 2006 and 2007 ART Testbed competitions do not make use of reputation exchange [Fullam, et al., 2006; ART Testbed, 2007]. Though interesting research advances still emerge from the competitions, this result is viewed as a weakness in the ART Testbed game design, since the ART Testbed is intended to serve as a forum for studying both experience- and reputation-based trust problems [Fullam, et al., 2005a]. The goal of this section is to 1) analyze why reputation exchange is not useful in the 2006 and 2007 competitions and 2) make recommendations, based on theoretical and empirical results from Chapter 3, for future changes to the ART Testbed game design to encourage reputation exchange. Through informal communication, members of the ART Testbed competition's organizing team have expressed enthusiastic interest in integrating the results of this research for future competitions.

Experimentation to identify game changes that encourage reputation exchange is complex. Existing agent designs from past competitions cannot be used in experiments, because those agents are not designed within the context of the new game rules. Competing agents must be designed to exploit the proposed rule changes, then resulting games must be observed to determine whether reputation exchange plays a role in appraisers' success. Competition is artificial if all competing appraiser agents are designed by a single researcher; results are dependent upon the quality of agent designs. The usefulness of reputation exchange is demonstrated if an agent whose strategy incorporates reputation exchange can achieve higher *NetProfit* than winning agents from past competitions; however, designing an agent that implements all strategy decisions required for success in the competition (including trustee-related decisions) is beyond the scope of this side discussion. The proposed game changes should be implemented in an actual competition setting to determine whether successful competitors make use of reputation exchange, but competition implementation is an impractical requirement given the time constraints of this research. Nevertheless, it is useful to make recommendations based on theory and experimentation in Chapter 3.

Experiments in Chapter 3 identify five influencers encouraging reputation exchange. These influencers indicate that appraisers should rely on reputation-based modeling to determine from which opinion providers to purchase opinions when:

Influencer 1: The number of opinion transaction observations (m) is low (Section 3.2.1),

Influencer 2: Opinion providers give inaccurate opinions, causing appraisers to transact less often and, therefore, obtain fewer transaction observations (Section 3.2.2),

Influencer 3: Opinion providers' opinion accuracy changes quickly, meaning the number of transaction observations (m) between changes never grows large (Section 3.2.3),

Influencer 4: Reputations are very accurate (Section 3.3.1), and

Influencer 5: Reputation cost is very low, relative to profit benefit from reputation acquisition (Section 3.3.2).

Decreasing the accuracy of opinion providers' appraisals (Influencer 2) is not a promising option for encouraging reputation exchange in the ART Testbed. First, game parameters cannot control opinion providers' decisions regarding c_g, the amount to invest in creating opinions. Second, when s^* and α are increased for all opinion providers, opinion error is likely to increase for all appraisers; since client allocations are dependent upon differences in appraisal error (not absolute magnitude of appraisal error), increasing s^* and α are likely to not affect appraisers' views of opinion providers' trustworthiness. Alternatively, if the range of s^* values is widened, the range of capabilities for producing accurate opinions is increased, and appraisers will transact with more accurate opinion providers while simply ignoring less accurate ones. Increasing the accuracy of reputations delivered by reputation providers (Influencer 4) is not a viable option, either, because reputation providers' decisions regarding reputation accuracy are not directly controllable by game parameters.

Section 4.3.1 and Section 4.3.2 describe how the 2007 competition, in an attempt to encourage reputation exchange, implements three changes to the game rules used in 2006 [ART Testbed, 2007]:

"Dummy" Agents: Fifteen dummy agents (five "cheating" agents, five "benevolent" agents, and five "neutral" agents) are added to each game to increase the total number of agents in the system (in an effort to activate Influencer 1 by slowing the number of observations per agent per timestep, assuming appraisers will purchase opinions from a limited number of opinion providers in each timestep). This game change fails to encourage reputation exchange because competitor appraisers select a subset of best opinion providers, and build up experience-based models about opinion providers in that subset, since expertise changes occur rarely.

Expertise Changes: Mid-game, unexpected expertise changes occur (zero, one, or two changes per game) in an effort to activate Influencer 3. This game change fails to encourage reputation exchange because appraisers still have many opportunities (approximately 200, 100, or 67 timesteps, on average) to observe transactions and, therefore, build experience-based models, between expertise changes.

Reputation Costs: Reputation cost is reduced from 1.0 to 0.1 in an effort to activate Influencer 5. This game change fails to encourage reputation exchange because appraisers have little need for reputations anyway, given the first two reasons; under these conditions, reputation cost is unimportant.

In an effort to slow the growth rate of an appraiser's number of opinion transactions with each opinion provider (Influencer 1), one might consider changing the game rules to conduct each game with a very large number of agents (as is the purpose of inserting dummy agents in the 2007 competition), either dummy agents or duplicates of competitors. In large systems with many dummy agents, an appraiser, who is limited by the opinion purchase cost in the number of opinions it can acquire, may be likely to select an adequate subset of opinion providers, building long-term experience-based models of the opinion providers in that subset. When duplicates of competitors are inserted to multiply the system size, the competition becomes susceptible to collusion among agents belonging to the same designer (a similar problem occurred during the 2004 Iterated Prisoner's Dilemma competition [Rogers, et al., 2007]).

A more viable option for encouraging reputation exchange is derived by examining the method by which agents might form both reputations to communicate to other appraisers and their own experience-based models. Because all appraisers begin the game with no trust models about other agents (acting as opinion providers), the reputations that appraisers provide to each other are inaccurate at the beginning of the game. However, reputations increase in accuracy over the course of the game (in the best case, when reputations are reported truthfully), until there is a change in the expertise of the opinion provider whose reputation is being discussed. At that time, reputations are again inaccurate but begin again to gain accuracy as each reputation provider observes more opinion transactions or receives more reputations. Increasing reputation accuracy is modeled in Section 3.3.1.1, where Figure 3-29 compares error of a truster's experience-based model and reputation-based model when $b_r = 2$ (the truster's reputation-based model is composed of twice as many transaction observations as its experience-based model). Figure 4-36 shows an extension of Figure 3-29, illustrating the error of a truster's experience-based model as compared against reputation models for which $b_r = 2$, 5, 10, and 20. When the truster relies on reputations representing many (for example, 2, 5, 10, or 20) transaction observations for each of its own transaction observations in its experience-based model, the truster's error is significantly reduced, especially early on, when it has only a few transaction observations building its experience-based model (for example, when m equals 1 to 10 as shown in Figure 4-36).

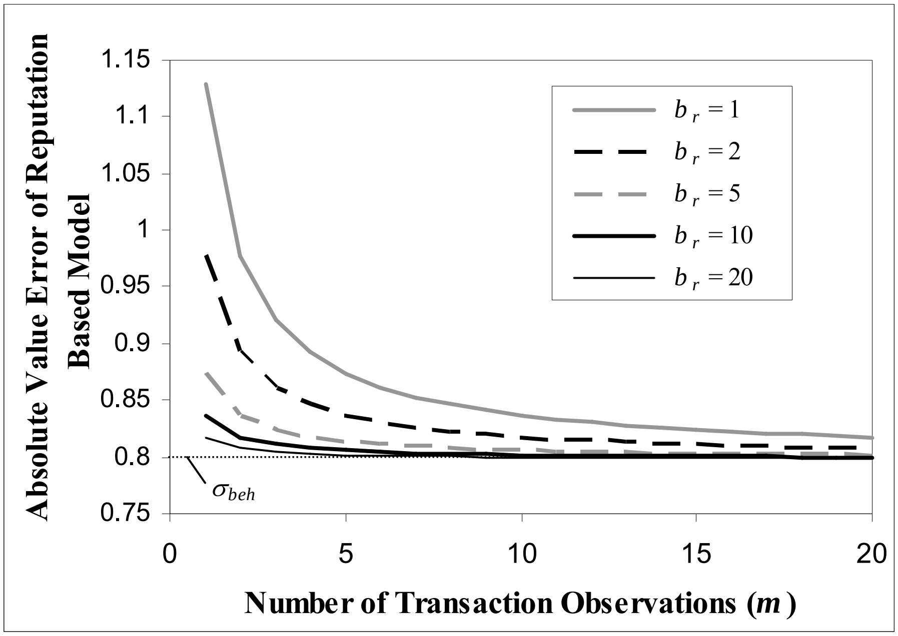


Figure 4-36. Theoretical comparison of aggregate suggestion absolute value error for an experience-based model (b_r = 1), as compared to reputation-based models (when b_r = 2, 5, 10, and 20) as number of transaction observations (m) increases. Absolute value error for trustee behavior (σ_{beh} = 1.0), the minimum achievable error, is shown as a baseline. For clarity, solid lines are shown (m is discrete).

A truster utilizing Adaptive Trust Modeling reduces its error further by combining both experience- and reputation-based models. Figure 4-37 shows theoretical weights of a truster's aggregate reputation-based model (assuming the truster weights experience- and reputation-based models according to Adaptive Trust Modeling) as a function of reputation-based model building factor (b_r). A truster is more likely to weight its reputation-based model highly if the model is built from multiple reputation suggestions for each of the truster's own transaction observations making up its experience-based model.

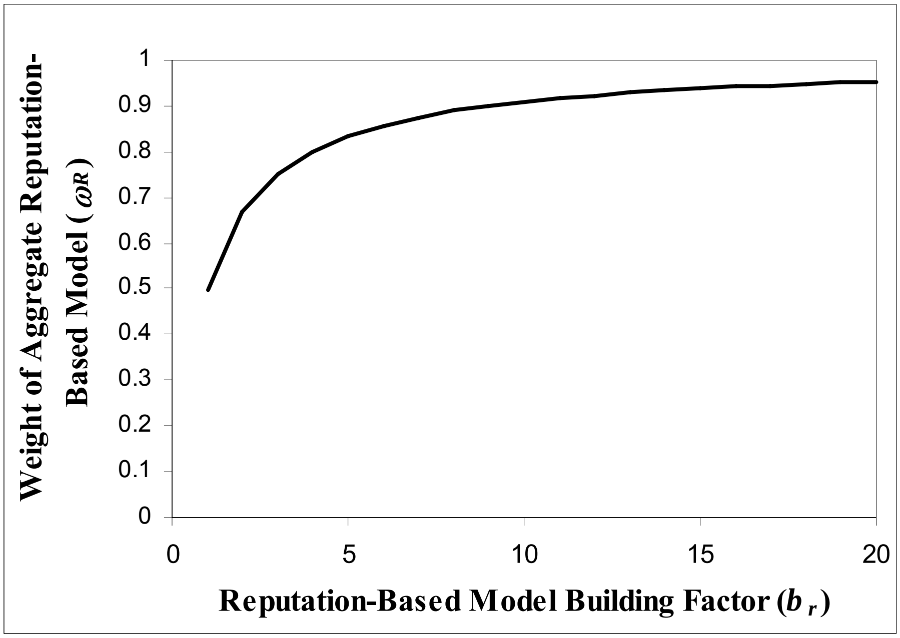


Figure 4-37. Theoretical weight of a truster's aggregate reputation-based model (assuming the truster weights experience- and reputation-based models according to Adaptive Trust Modeling) vs. reputation-based model building factor (b_r).

To encourage reputation exchange in the ART Testbed competition, game rules should ensure that opinion providers' expertise changes often enough to ensure that the accuracy of an appraiser's potential reputation-based model (depending on b_r) is consistently significantly higher than that of its experience-based model, As shown in Figure 4-36, reputation-based models are most advantageous when m is small; this notion is reinforced by Figure 3-23 in Section 3.2.3, which shows that experience-based model weight decreases (reputation-based model weight increases) as the number of observation opportunities between trustee behavior changes (m_{max}) decreases. As m increases, the difference in accuracy between an appraiser's reputation- vs. experience-based model decreases until the cost of purchasing reputations outweighs the benefit of increased accuracy and client share gain. Further, it must be remembered that a single reputation (with respect to a given era) impacts opinion-purchasing decisions regarding numerous clients in each timestep (an appraiser's number of clients in a timestep with same-era paintings is equal to the appraiser's client share divided by the number of eras, on average). Therefore, a reputation's *MarginalReward* (and cost c_r the appraiser is willing to pay) is significantly large if the number of eras is small. Reputation cost (c_r) should be set low enough to encourage appraisers to purchase reputations, yet high enough to give reputation providers an incentive to report truthful reputations (determination of an appropriate c_r value requires experimentation).

In summary, game rules for previous ART Testbed competitions have failed to encourage reputation exchange among competing agents. Even recent suggestions from ART Testbed competition organizers ([Gomez, et al., 2007]) for game rule changes have failed to identify the suggestions presented here. However, theoretical and empirical results from Chapter 3, identifying environmental factors influencing the effectiveness of experience- vs. reputation-based trust modeling, provide clues for improving ART Testbed game rules for future competitions. It is hypothesized that reputation exchange is encouraged in the ART Testbed by 1) enforcing frequent expertise changes (to limit the maximum number of transaction observations building up experience-based models) and 2) selecting an appropriate value for reputation cost (low enough to encourage purchasing but high enough to encourage communication of accurate reputations).

Chapter 5

CONCLUSIONS

This research presents 1) Adaptive Trust Modeling for identifying how trusters may utilize both experience- and reputation-based trust modeling to achieve the most effective decision-making tool possible and 2) Adaptive Cost Selection for valuating and purchasing trust information. This chapter summarizes the research presented, enumerates its contributions, and outlines possible future extensions and applications.

5.1 Research Summary

This research explores the following hypothesis: *Experience- and reputation-based trust models can be integrated to yield an aggregate trust model more accurate and cost-effective than either single model.* Chapter 3 examines how conditions of a truster's environment impact its reliance on experience- vs. reputation-based trust modeling (Research Question 1), introducing the Adaptive Trust Modeling technique, by which a truster can optimally utilize both experience- and reputation-based modeling to achieve an aggregate model more accurate than either single model. Chapter 4 introduces Adaptive Cost Selection, answering the question of how trust information should be valuated to assist a truster in acquiring trust information at a cost (Research Question 2).

5.1.1 Research Question 1: Environment Characteristics Influencing Experience- and Reputation-Based Models

Research Question 1 asks: *How do characteristics of a truster's environment affect the usefulness of the truster's experience- and reputation-based models?* Chapter 3 answers this research question through Adaptive Trust Modeling (Section 3.1), a technique for weighing the accuracy of experience- and reputation-based trust models. Adaptive Trust Modeling combines the two models for a more accurate aggregate model than using either single model or simply averaging, as demonstrated theoretically in Section 3.1.4. Further, experiments show that Adaptive Trust Modeling achieves an aggregate model with greater accuracy than either experience- or reputation-based modeling alone across a wide range of system conditions, with variations in 1) availability of transaction observation opportunities (Section 3.2.1), 2) trustee trustworthiness dynamics (Section 3.2.2 and Section 3.2.3), 3) accuracy of available reputations (Section 3.3.1), and 4) cost of available reputations (Section 3.3.2). The Error-Sensitive Translation technique described in Section 3.3.1.2 improves the usability of reputations from providers who are inaccurate, yet consistent, in the reputations they deliver. Examination of experience- and reputation-based model weights assigned by Adaptive Trust Modeling given these varying system conditions reveal that the weight of a truster's experience-based model increases as:

1) The number of transactions (m) with the trustee, as observed by the truster, increases, since the truster is better able to model trustee behavior with more observations (Section 3.2.1),
2) Trustee trustworthiness (μ_{beh}) increases, since the truster is more likely to conduct transactions (and gain observations) if the trustee is perceived to be more trustworthy (Section 3.2.2), and
3) The frequency of the trustee's behavior change (changes in μ_{beh}) decreases, since the truster is able to obtain more observations between changes (Section 3.2.3).

Further, the weight of a truster's reputation-based model increases as:

1) The accuracy ($\sigma_{R,sug}$) of that reputation-based model increases (Section 3.3.1) and
2) The cost ($Cost(R_i)$) of purchasing reputations decreases, since the truster is able to purchase more reputations, which yield a more accurate, aggregated reputation-based model (Section 3.3.2).

The experimental results of Chapter 3 refute the first three misconceptions identified in Section 1.4. Misconception 1 states: "Large systems (with many trusters/trustees) always make experience-based modeling ineffective." From Section 3.2.1, a truster's experience-based model is effective as long as the truster continually observes enough transactions with each trustee it considers (in other words, if m reaches a high number, between changes in trustee behavior, μ_{beh}, relative to the accuracy, $\sigma_{R,sug}$, of the truster's reputation-based trust model). Misconception 2 states: "Infrequent transactions always make experience-based modeling ineffective." From Section 3.2.3, a truster's experience-based model is effective as long as the truster observes transactions more frequently than the trustee changes its trustworthiness behavior pattern (in other words, if m reaches a high number, between changes in trustee behavior, μ_{beh}).

Misconception 3 states: "Inaccurate reputation providers are never useful." The Error-Sensitive Translation technique described in Section 3.3.1.2 improves the usability of reputations from providers who are inaccurate, yet consistent, in the reputations they deliver. Finally, the experimental results provide a practical application by identifying rule change suggestions for the ART Testbed competition with the purpose of encouraging reputation exchange among competing agents.

5.1.2 Research Question 2: Assessing Trust Information Value

Research Question 2 asks: *How should a truster assess the value of trust information (specifically, reputations), in light of the cost of that information, to determine what trust information to acquire?* Chapter 4 answers this research question through Adaptive Cost Selection (Section 4.1), a technique for valuating pieces of trust information (specifically, reputations) based on the marginal aggregate model accuracy they contribute and resulting increase in the truster's average payoff. By understanding the value of trust information, a truster can make decisions about the amount of risk exposure to accept (in terms of its transaction outlay) relative to expected net transaction payoff, given the truster's amount of trust information available (Section 4.1.5). Experiments in Section 4.2.1 demonstrate that Adaptive Cost Selection achieves net payoff (transaction payoff minus reputation costs) equal to that of the best fixed-quantity selection strategy over a wide range of possible reputation cost values, $Cost(R_i)$. When the truster has access to a free experience-based trust model, in addition to purchased reputations, Adaptive Cost Selection purchases an efficient number of reputations, decreasing the number of reputations purchased as the accuracy of its experience-based model increases. Further, experiments in Section 4.2.2 show that Adaptive Cost Selection need not rely on assumptions about average trustee behavior distributions. By approximating average trustee behavior distributions over time, Adaptive Cost Selection achieves net payoff nearly as high as when average trustee behavior distributions are known. In Section 4.3, Adaptive Cost Selection is applied to the ART Testbed domain problem, demonstrating that an agent employing Adaptive Cost Selection achieves higher total profits when competing against an agent not using Adaptive Cost Selection across a wide range of information cost values.

The experimental results of Chapter 4 refute the last three misconceptions identified in Section 1.4. Misconception 4 states: "A truster can rely on experience-based modeling for low-value transactions, but should always acquire reputations when considering high-value transactions." Experiments in Section 3.3.1 and Section 3.3.2 show that both cost and accuracy of trust information should influence the truster's decision to acquire trust information. Misconception 5 states: "A truster should always acquire only the single or few 'best' reputations." Experiments in Section 3.3.2 show that the appropriate number of reputations to purchase depends on not only the accuracy of each reputation, but also on reputation cost and the availability of other free trust information (e.g. an experience-based model); when reputations are free or inexpensive (compared to the expected transaction payoff), a truster benefits from acquiring many reputations. Misconception 6 states: "A truster should always rely on reputation-based modeling when it has no experience with a trustee." Section Section 4.1.5 demonstrates that when reputation costs are prohibitive, a truster may have decide whether to trust based on no trust information at all, basing its decision on the transaction's risk.

5.2 Contributions

This research makes the following contributions to the field of agent trust research:

Dynamic utilization of experience- and reputation-based trust models for effective trust-based decision-making: The agent trust research field has traditionally viewed experience- and reputation-based trust modeling as incompatible trust assessment techniques for disparate environments, as evidenced by research regarding one-to-one games [Crandall and Goodrich, 2004; Biswas, et al., 1999], which ignores the opportunity for reputation exchange, vs. referral networks [Yolum and Singh, 2003] and online reputation mechanisms [Dellarocas, 2000] which assume trusters have few opportunities for repeated transactions. Recent work acknowledges scenarios in which both experience- and reputation-based trust assessment are useful, but techniques for combining both types of models are limited to static weighting [Barber and Kim, 2003] or rely on manual weight assignment based on the human designer's intuition [Huynh, et al., 2004; Ramchurn, et al., 2004]. In contrast, Adaptive Trust Modeling enables a truster to dynamically and automatically adapt its reliance on experience- or reputation-based trust as system conditions change. Adaptive Trust Modeling transitions smoothly along the spectrum of experience- and reputation-based trust model utilization by translating environment factors (availability of transaction observation opportunities, trustee trustworthiness dynamics, accuracy of available reputation providers, and cost of acquiring reputations) into influencers of trust model accuracy.

Quantitative analysis of experience- and reputation-based model tradeoffs for strategic trust modeling building: Humans often have an intuitive notion about the most appropriate type of trust modeling to use in a given environment. However, the misconceptions outlined in Section 1.4 and the shortcomings of the ART Testbed game problem design (in failing to ensure the necessity of reputation exchange in successful strategies [Fullam, et al., 2006]) demonstrate how humans make mistakes in determining when to use experiences vs. reputations. Further, humans have difficulty dealing with the ambiguity of questions (from Section 1.1) such as 1) When is transaction experience sufficient enough to rely on an experience-based model? 2) How frequently may a trustee change its behavior pattern yet still be accurately modeled by experiences? 3) How accurate must provided reputations be to make reputation-based modeling advantageous? 4) At what point do reputations become too expensive to make reputation-based modeling feasible? A quantitative analysis of the tradeoffs between experience- and reputation-based models eliminates misconceptions about both model types, providing human trusters with intuitive explanations for when each type of trust modeling, experience- and reputation-based, is most appropriate. Adaptive Trust Modeling computes the optimal combination of experience- and reputation-based trust information to produce the most accurate aggregate model possible. Further, analysis of experience- and reputation-encouraging environment factors empowers agents to make trust-related decisions to acquire the types of trust information they can utilize best. If a truster has control over building its experience- and reputation-based models, knowing the system conditions conducive to each type of model instructs the truster about which type of model to invest in building. An individual who benefits from a specific type of trust modeling may seek out (or even influence) specific system conditions to encourage its preferred trust modeling technique.

Valuation of trust information for cost-based reputation selection: Other research acknowledges the cost to produce trust information [Avery, et al., 1999], noting that cost of trust information acquisition should be minimized [Ghanea-Hercock, 2004]. Incentive compatible mechanisms for reputation exchange [Jurca and Faltings, 2006; Huynh, et al., 2006] minimize a truster's effort to acquire trust information, but do not address a truster's problem of valuating trust information of varying accuracy. Instead, Adaptive Cost Selection assesses the value of trust information, enabling a truster to analyze the cost vs. benefit of acquiring that trust information. Adaptive Cost Selection is unique because it correlates trust model accuracy to transaction payoff, valuating trust information based on the marginal aggregate model accuracy increase attributable to a single piece of trust information. By knowing the worth of a given piece of trust information, a truster can decide how much time, effort, and money it is willing to invest to acquire that information. Further, Adaptive Cost Selection assists reputation providers in setting reputation costs, and trusters in negotiating reputation costs, when those costs are flexible. The Adaptive Cost Selection algorithm described in this research assesses the value of individual pieces of trust information (in particular, reputations), with the understanding that trust information may have varying degrees of accuracy. Adaptive Cost Selection minimizes the truster's costs when acquiring trust information by determining exactly how much and which trust information to acquire. Further, the algorithm identifies the optimal tradeoff between aggregate trust model accuracy and cost of acquired trust information to maximize the truster's payoff from transactions with trustees.

This research produces tools to aid both human and agent decision-makers in determining when to trust. Adaptive Trust Modeling and Adaptive Cost Selection enable software agents to dynamically change modeling techniques based on varying environment factors. Further, these technologies assist human users in complex trusting domains, computing the most effective combination of experience- and reputation-based trust modeling for given system conditions.

5.3 Future Extensions and Application

The investigations presented here pave the way for numerous research extensions. First, Adaptive Trust Modeling calculations assume trustee behavior and trust model suggestions follow normal distributions. While these assumptions are reasonable in many cases, future work can extend the types of distributions accommodated with more complicated computation. Second, this research examines the links between only two types of trust modeling. While experience- and reputation-based modeling approaches are two of the most well-studied trust modeling techniques in the agent trust research community, integration of other techniques, including group association and credentials, should be explored. As an underlying theme, this research demonstrates that scenarios exist in which changing system conditions make necessary the use of multiple trust modeling types; additional trust modeling techniques can strengthen truster decision-making in scenarios for which experiences and reputations fall short. For example, when reputations are inaccurate and a truster has had no previous experiences with a potential trustee (e.g. the trustee is a medical doctor new to town with no previous patients), if the truster maintains trust models about trustees similar to the trustee in question, the truster may use group association make decisions regarding that trustee (the medical group practice to which the doctor belongs is well-known). Further, if the truster has no experience with or reputations about any trustees in the system whatsoever, the truster will improve the quality of its trusting decisions if credentials are available for verifying the trustworthiness of the trustee (the doctor's medical school records verify his capabilities).

In addition, future work should examine limitations of Adaptive Trust Modeling. If an adversarial trustee knows the truster's Adaptive Trust Modeling algorithm, it might attempt to cheat the truster, for example, by allowing the truster to build a very confident experience-based model (indicating high trustee trustworthiness), only to unexpectedly cheat later on in a single, large-value transaction. Adaptive Trust Modeling provides robustness, helping prevent this scenario by enabling a truster to rely on both experience and reputation. Further, risk assessment strategies as discussed in Section 4.1.5 (conducting small-value transactions until trust models are sufficiently accurate) help limit transaction losses. Nevertheless, Adaptive Trust Modeling is only as accurate as its experience- and reputation-based models and its estimates of their error. Future work must identify ways to thwart these strategic trustee cheating techniques.

The Adaptive Cost Selection technique for valuating trust information provides insights into future work regarding reputation price negotiation. Adaptive Cost Selection enables a truster to estimate the utility of each available reputation, then perform a cost-benefit assessment with regard to each potential reputation purchase. Therefore, trusters can use their utility estimates as guides when proposing prices they are willing to pay in negotiable-cost reputation markets. Strategies similar to Adaptive Cost Selection can be explored for application by reputation brokers, who may use utility estimates for price-setting. Risk-management techniques can be investigated in scenarios in which a truster may determine the outlay it is willing to based on the transaction's risk, as measured by the amount of trust information it has acquired.

Finally, this research provides tools to overcome weaknesses in human trust decision-making regarding when to use experience- vs. reputation-based trust assessment. Humans frequently make mistakes when evaluating the trustworthiness of potential trustees, perhaps due to naïveté, irrationality, or emotion. A natural extension of this work explores applications in which humans interact with the technology presented in this research. For example, Adaptive Trust Modeling can be implemented in environments such as online social networks, where both experience- and reputation-based trust modeling assist users in forming relationships. Adaptive Cost Selection can be implemented for evaluating cost-appropriate recommendations from fee-based online referrals services. Future research must address implementation issues; each tool must be introduced to the human user such that the user will 1) recognize the advantage of using the tool (motivation), 2) take time to use the tool (user-friendliness), and 3) follow the technology's decisions over the human's (confidence). This research makes an important contribution in laying the groundwork for future extensions and applications.

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